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AI, Decision-making and Sharing Economy

How AI Affects Decision-making in P2P House Rental Context

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It is not enough to have a good mind. The main thing is to use it well.

—René Descartes, *Le Discours de la Méthode*

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Abbreviations

AI	Artificial Intelligence
ANOVA	Analysis of Variance
P2P	Peer-to-peer

Abstract

Sharing economy and platform business models respectively, are increasingly gaining position both in our society and today's academia and managerial world. Though, it is not clear whether the platform entrepreneurs tend to rely on intuitive and/or analytical approaches when they set prices for their offerings in these contexts. In brief, the process models that people apply in their reasoning and decision-making practices in the mentioned context are unclear as well as the impact of different factors and characteristics such as gender. To these ends, this study aims at contributing to this gap by analyzing the results of an experimental survey/game, which assesses humans' decision-making in a short-term house rental platform context, with and without the influence of AI. Through constructing a theoretical model that assesses human decision-making, it is possible to analyze different types of approaches to price determination in the experimental platform context. Performance therein is considered as a function of analytical skills and strategic intelligence. The Kruskal-Wallis test is used as the statistical tool to test the theoretical claims and hypotheses made.

The findings of the study support the division between analytical and intuitive skills as made in the theoretical model: the best performing players of the game are notably more analytical in their approach when compared to those performing the worst. Additionally, the results support the claim that the involvement of artificial intelligence renders void the traditional competitive strategy based on the assumption that customers independently determine their willingness to pay for a product or service, and that the hosts would be free to value their offerings as they like. Rather, when AI is involved, it is no longer a question of pure supply and demand but the individuals become rather inherent components of a wider strategic plan of a corporation behind the platform: the supply and demand are artificially manipulated and engineered. Consequently, the thesis aims at providing insights for both platform entrepreneurs and managers facing the challenge of value creation and capturing in the mentioned contexts.

2. Introduction

As of today, there does not seem to be too many contributions on the precise interplay of AI, decision-making, and price determination in the P2P context. Especially so this appears to be in respect to the strategy and approach that would seem to precede and predict the success of platform entrepreneurs in P2P markets (Gibbs *et al*., 2018; Chattopadhyay & Mitra, 2020). Related to this, it is considered that even if strategic decision-making is generally recognized as a result of both intuitive and analytical thinking and reasoning, their interplay is largely dismissed when performance is assessed and analyzed (Calabretta *et al*., 2017). Particularly, when it comes to cognitive literature on entrepreneurial ventures and contexts. Consequently, a gap can be recognized in the role and value of intuition in entrepreneurial decision-making. This is noteworthy when the broader psychology and management literature are considered since they systematically tend to indicate how intuition is a more prevalent way to decide by being more effective in uncertain environments – just like in those of P2P markets (Baldacchino *et al*., 2015, p. 213).

For these reasons, by exploiting the Kruskal-Wallis test, this thesis aims at analyzing the role of analytical skills and strategic intelligence in respect to performance on a short-term house rental platform. In other words, analytical skills and strategic intelligence are treated as independent variables and they are assessed through the different scenarios that the players face in the game. The performance is assessed through the profits and customer value that the players will produce therein. For the analysis, these are treated as the dependent variables. The essence and nature of both the analytical and strategic skills are defined through a theoretical model inspired by the one presented in the study of Levain *et al*. (2017, p.2404).

The data analyzed in this thesis is collected through a survey/game that is a part of a wider research and study on human-decision making and AI in the sharing economy context, conducted by Evangelos Syrigos. Technically, the survey/game has consisted of two parts that each respondent has gone through: first, a self-assessment assessing the level of analytical and intuitive tendencies of the respondent, followed by a game where the respondents have acted as a host of a holiday home on a P2P platform, just like that of Airbnb. The task of the hosts has been to determine the price and number of amenities they wish to choose for their lodging. The game part is built as a randomized experiment: there are two different main versions with different sub-scenarios. Depending on the type of game and scenario that the player faces, s/he is encouraged to approach the price determination dilemma in a certain way. In this thesis, the experimental game is often referred to as the first and second experiments. In the first experiment, the focus is only on human decision-making and different potential approaches to it (intuitive, analytical, both, or nothing). In the second experiment, the focus is on the involvement of AI and its impact on humans' reasoning process. The experiment will be explained in more detail in chapter four of this thesis.

Finally, the analytical part of this study is inspired and supported by several studies and pieces of research: the study from Levain *et al*. (2017) has given inspiration for the theoretical model and assessment of performance. Additionally, the 'manuscript' to the research conducted by Evangelos Syrigos on the mental processes in entrepreneurial decision-making has worked as a sort of support for the hypothesis drafting and the overall approach adopted in this thesis. Another piece of study that has notably shaped the arguments and approach taken in this thesis has been the study conducted by Baldacchino *et al*. (2015) on '*Entrepreneurship Research on Intuition'*. Nonetheless, a considerable amount of other articles and researches have been gone through to support the flow of arguments in this thesis, which are listed in the references.

The Main Research Question

The main idea of this study is to both analyze what type of decision-making process and approach seem to precede success in P2P house rental platforms, if any, and what is the impact of AI in the reasoning process. By addressing these questions, it will be eventually possible to discuss the implied insights for both the platform entrepreneurs and managers overseeing these types of platforms, and to discuss what are the overall contributions to the strategic management theory.

This thesis illustrates one way of modeling human reasoning and decision-making processes through the defined theoretical model in a competitive environment. It will be observed whether AI seems to improve/optimize the performance and human reasoning processes and if so, is it through completely automated processing of data or augmentation of the human-driven processes. Consequently, the study aims at answering the following question: '*How AI affects decision-making processes in the P2P house rental context*'. Additionally, as a sort of secondary interest, it will be observed whether there seems to be a divergence between male and female respondents in terms of performance.

Outline

The structure and the flow of arguments in this thesis are as follow:

In chapter three the essential definitions and concepts, which are crucial for understanding the study are laid out. Additionally, the theoretical model that works as a framework and a point of reference for the subsequent results is introduced. At the end of the chapter, the hypotheses are presented.

Chapter four presents the experimental design and methodology. The experiment is explained in more detail and the summary statistics regarding the respondents are introduced. The approach taken to the statical analysis is explained and how it fits with the conducted experiment and the collected data.

In chapter five, the focus is on the elaboration of the statical tests done for this study. However, in-depth discussion and demonstration of the mathematical theory behind the tests are beyond the contents of this study. Though, appropriate references are given when considered essential, and the codes used for computing the tests in RStudio software can be found in appendix 5. Altogether, this chapter demonstrates the relationship between the theoretical framework, the different variables of the game, and the statistical analyses.

A constrained optimization problem is built-in chapter six to determine the (possibly) best and worst-performing players. By building a function that enables to find the optimal price and number of amenities, it is possible to further analyze the responses and self-assessments of the players within the constructed theoretical framework. In brief, the actual results of the game are reported and it will be concluded whether they seem to support or reject (some) of the drawn hypotheses.

Finally, chapter seven discusses in entirety the results and theory and examines whether there is enough evidence to reject the null hypotheses. The managerial implications are addressed. Conclusions and final remarks are made in chapter eight.

3. Theoretical Background

In this chapter, the conceptual framework and the theoretical model are introduced together with the hypotheses, which provide the approach for the subsequent analyses and results. First, the essential concepts for understanding the study in this thesis are briefly covered, followed by the introduction of the theoretical model that has been used as the approach to cluster the collected data and make sense out of it. Finally, the reasoning behind the drafted hypotheses is presented.

3.1 Concepts and Definitions

3.1.1 Human Decision-making

According to Hodgkinson and Sadler-Smith (2018), human reasoning and information processing is a product of an analytical rational system and that of an intuitive experimental system. Moreover, these systems are deemed to operate parallel in a harmonious and synergetic way but occasionally conflicts may arise, causing ‘a struggle between feelings and thoughts’. It is observed to be dependent on the individual and/or the situation at hand, which ultimately determines which system has a higher weight in the reasoning and decision-making processes. Overall, human decision-making is seen as an interplay of reflexive (intuition) and reflective (analysis) processing (Einhorn, 2021). In a recent article from Harvard Business Review, decision-making is described as a circular process, emphasizing the importance of the interplay of the mentioned two (Einhorn, 2021).

Consequently, humans make decisions through simplified models, which are often in the everyday language referred to as rules of thumbs or heuristics, implying that humans’ rationality is technically bounded by nature (Simon, 1987). According to Simon (1987), the rules of thumb i.e. bounded rationality represent stored information and experience that is often unconscious and thus people tend to rely at least partly on intuition while making decisions. In other words, if intuition that is considered as stored information and experiences forms the bounded rationality for which humans are subjects, then each decision a human makes is a function of intuition and analysis. Of course, the extent and magnitude of these variables vary depending on the type of decision at hand and the particular human being in question. It follows that the question on decision-making is ultimately about the degree of intuition and intention on a continuum of rationality. In general, humans can be classified as consistently intuitive or consistently analytical in information gathering and evaluation (Abubakar *et al*., 2019), which supports the classification between the system 1 and system 2; humans reason and decide based on non-conscious and conscious processes (Kahneman, 1991).

Be as it may, it is evident that human brains are inflicted with a myriad of cognitive biases that affect negatively the ability to exercise judgment in predictable ways. Humans are indeed able to make quick and almost unconscious decisions but this does not imply optimality and accuracy (Einhorn, 2021). For that reason, we need data and something external such as AI to help our brains in the decision-making process to reach a higher level of accuracy and efficiency (Colson, 2019). However, it is noted that even when humans rely on the help of data it is not enough to break from all the cognitive biases and the fact that humans are not able to leverage all the data. In instances where humans are required to conduct so-called scenario analysis and reasoning (also known as the what-if analysis) the number of scenarios may cause the decision-maker to a state of so-called combinatorial explosion where it is somewhat impossible to fully grasp all the diverse scenarios and their possible consequences and interplay, which may lead to potentially irrational outcomes (Einhorn, 2021; Colson 2019).

3.1.2 AI

Generally speaking, AI refers to technology executing algorithms that replicate humans' cognitive processes and reasoning (Pomerol, 1996). It is used to perform cognitive functions such as problem-solving, learning, reasoning, and perceiving similarly to the human mind (McKinsey & Company, 2018).

Additionally, there are at least two general types of AI that can be distinguished: i) the process of modeling and creating computer-based artifacts for the execution of different types of human tasks and, ii) the process of design and development of systems that mimic (subjective) human beings. Though, in this respect and especially in the context of decision-making, it should be noted that there is an ongoing debate on the genericity and subjectivity of AI's decision-making approach: do humans decide by following a similar, rational path, or is the process different for every human being (Pomerol, 1996)?

Another noteworthy dimension of AI, relevant for this thesis, is the way how AI is used and relied on. In this thesis, the interest will be on AI-driven processes that are either automated, meaning humans have no role in the process, and on processes that are augmented by AI i.e. the role of AI is to assist humans in their decision-making processes but not to replace them entirely (Chojecki, 2020). In short, ultimately it is all about the question of an optimal degree of automated reasoning, which is about the ability to provide proof of logic for any type of computational problem without human involvement (Banerjee *et al*., 2018).

3.1.3 Human – Machine Collaboration; A System of Intelligence

In respect to the instances where humans make decisions with the help of AI, it should be born in mind what has already been said on the bounded rationality of humans and their tendency to simplify things. In other words, humans and machines are not comparable in intelligence. They rather augment each other (Trunk *et al*., 2020). Therefore, the aim of using AI in decision-making processes is to increase efficiency and profitability by reaching the apex of rationality. In short, due to humans' bounded rationality, the highest possible level of rationality cannot be reached unless technology is involved in the process. By augmenting the process with AI, a state in which humans' rationality has become unbounded for the ends of efficiency and control can ultimately be reached. For the time being, this seems to be the only way to 'freedom' from the inherently biased human mind (Lindebaum, D. *et al*., 2020). Consequently, evolvement from data-driven to AI-driven decision-making is needed since human intuition alone is far from the ideal tool, which is required for efficient reasoning and decision-making, as noted above. This is especially so because humans tend to make decisions based on subjective-objective rationality, which is to say that one's values, culture, and strategic context affect the type of observations and decisions that one eventually makes (Colson, 2019). However, regardless of the advances in AI and the inherent benefits, it brings for businesses and decision-making, it should be nonetheless kept in mind that AI is not a fast-track to success, which would enable one to ignore the variables of decision-making and simply get ready-made solutions. It is pivotal that one understands the process, its inputs, and outputs in order to fully exploit the technology (Chojecki, 2020).

Altogether, it can be derived from the above said that when humans make decisions by relying on AI, we are talking about an entire system of intelligence that combines software in terms of algorithms, machine learning codes, and predictive analysis but also about hardware, data, and human input (Frank *et al*., 2017). It is this system that is the focus and interest of this thesis, and ultimately the defining factor for success in the P2P house rental contexts.

3.1.4 Sharing Economy and Platform Business Models

In general, platform businesses can be defined as two-sided networks constructing a marketplace that provides infrastructure and rules, bringing together the market participants.

Namely, the producers and consumers; the products, services, and customers (Eisenmann *et al*., 2020; Church, 2017). In general terms, sharing economy is used when it is referred to a myriad of these types of platforms, which is considered as a new way of organizing economic activity, posing a threat of superseding traditional corporates and businesses (Sundararajan, 2016, abstract).

Logically, if something is to supplant the *status quo* of making business, new ways of pricing and producing value must be present. According to Van Alstyne *et al*. (2020), the shift from pipeline type of value chain to that of the platform includes three notable steps: a shift from i) resource control to resource orchestration, ii) internal optimization to external interaction and, iii) customer value to a focus on ecosystem value. Overall, platforms are about creating and maximizing the total value of the ecosystem, thus making the process and value chain a circular, iterative one instead of the traditional linear one. Consequently, what this means for platforms like Airbnb and the process of price determination therein, is that new performance metrics are present and the price determination must take more variables into account, the prices being much more dynamic and volatile. A need for a change of strategy is implied (Van Alstyne *et al*., 2020; Sedkaoui & Khelfaoui, 2020).

Finally, it should be noted that in this thesis it is talked about sharing economy in general terms but the experiment and reasoning which follow are only studied and observed precisely in the P2P short-term house rental platform context. Therefore, the subsequent analysis and discussion will most likely have analogical value on the Airbnb platform but whether the results and analysis would also hold in other P2P platforms is not assumed by definition but it is something that is left for subsequent studies to investigate.

3.1.4.1 Short-Term House Rental Platforms

The game/simulation on human decision-making and AI, which has produced the data for this thesis, happens on a fictional online marketplace for short-term apartment rental. The platform can be considered similar to Airbnb, meaning that Airbnb forms a valid example and a point of reference for this thesis. In general, what is so particular about these platforms is the fact that all the real estate listings on their websites are not owned by the company running the platform. The platform merely brings together the supply and demand, the owner and the customer. The role of the platform is to operate as a broker, and it is therefore up to the owners to decide what type of apartments they offer and with what kind of amenities. Consequently, it is the listing attributes and services offered for properties, which influence the decision-making processes of the prospective guests (Chattopadhya & Mitra, 2020).

3.1.5 Dynamic Pricing Strategies in the Sharing Economy Context

Conventionally, pricing is considered as a somewhat uncomplicated and straightforward process by determining an optimal price level based on supply and demand so that the revenues are high enough to cover the costs and make some profit while being low enough to attract customers (Cöster *et al*., 2020, p.12). There are different methods and strategies to set the price i.e. different pricing strategies. Theories referring to instances in which businesses set flexible prices for products and services, depending on the current conditions in the market are so-called dynamic pricing strategies. One such strategy is the value-based pricing method that bases the prices on the price elasticity of a product/service (Gibbs *et al*., 2018). In other words, (potential) customers have varying valuations for different products and services, meaning that it depends on a person how much they are ready to pay for a certain product/service. Therefore, this strategy roots the price on the public perception of value and adjusts according to the collective view (Smith, 2016, p.17). Consequently, it would seem logical to assume that this would be the primary strategy that hosts on short-term house rental platforms rely on when defining and deciding their lodgings' prices but whether this is the case this will be seen later.

In practice, though, the competition and the different variables and their interplay are not so self-evident and predictable. For these reasons, various studies have focused and specified on the way how Airbnb hosts approach the pricing issue and how Airbnb's own algorithmic pricing suggestions seem to be formed. For example, Gibbs *et al*. (2018) studies the pricing on Airbnb through the hedonic pricing model theory that assumes a price being a function of measurable utility-affecting attributes or characteristics of a product/service. This further implies that the price of accommodation, such as one provided and offered through the Airbnb platform, is a combination of all the different amenities that affect the overall quality and perceivable value of the lodging. Overall, Gibbs *et al*. (2018) provide an approach for the hosts' pricing process analysis, which would enable them to increase revenues. Thus, if this model and the line of reasoning hold, it follows that the ultimate prices that the hosts set can be considered as a result of multiple regression analysis, meaning that it reflects hosts' assumptions on marginal implicit prices of some particular amenities. Though, in the study, it is noted that whether a place will be booked through a platform such as Airbnb is not a direct response to the price but factors like location and size matter significantly (Smith, 2016, p.17;

Chattopadhya & Mitra, 2020, p.602). This is further confirmed by Chattopadhya and Mitra (2020) by studying the similar hedonic pricing model as used by the traditional hotel service sector. In practice, this means that the individual attributes and amenities do not have pre-determined prices and value but their market prices are largely dependent on the specific bundle that is combined with them in addition to space and time where they are offered. Eventually, what this all means is that in the context of the digital sharing economy, the price determination does not follow *prima facie* any specific pricing theory but the final price is a result of the non-linear influence of listing variables on room pricing, in a dynamic short-term house rental market. Of course, if the price has not been automatically set by the service enabler. Thus, the key in this respect for platform entrepreneurs lays in the identification of the variables that appear to be the key determinants of tourist accommodation prices (Chattopadhya & Mitra, 2020).

3.1.6 Network and Community Management

After having defined the concepts of sharing economy and platform, few notations should be made on the way performance is measured in these contexts. Though, as has been said in the previous preceding chapter, the value chain on platforms like Airbnb is not the traditional pipeline one but the process of creating and producing value is rather an iterate, circular one (Van Alstyne *et al*., 2020). Inherently, this raises a question on the definition of optimal performance and from whose point of view that is even measured. Overall, there must be an incentive for hosts to stay on the platform but equally a reason for customers to come there because the value proposition is something more convenient than found elsewhere. Ultimately, it is a challenge for platform managers on the corporate level to try to manage the network and its offerings in a way that balances the interests of all the parties involved (Church, 2017; Kumar *et al*., 2018). It is emphasized by Habibi *et al*. (2017) in their study that in the sharing economy business context managers should focus on the community growth but respectively emphasize socialization, sustainability and avoid references to money and calculations (Habibi *et al*., 2017). Overall, some threats the platform providing companies face if they do not adequately balance the interests include inconsistent service performance, supply shocks from service providers, and price-sensitive switching customers. What this implies is that without addressing and identifying particular problems for each platform participant, sustainable profitability cannot be achieved (Kumar *et al*., 2018). Consequently, holistic community management should be seen as the enabler and way to long-term profitability (Accenture Strategy).

3.2 Theoretical Model

After having defined in general the essential concepts for the understanding of this study, a more precise framework will be drafted to guide the later clustering and analysis of the data. In the following sub-sections, the components of the theoretical model are going to be specified. The actual data analysis will be conducted in chapter five. The theoretical model that follows is inspired by the study conducted by Levain *et al.* (2017).

Overall, the data collected through the survey/game will be analyzed through the players' performance that is considered to be the number of profits that a host managed to get in the game, given that s/he managed to rent his/her holiday apartment (the formula for defining profits for hosts is the following: *price - (# of amenities x 20)* and the utility that a customer gets: *(# of amenities x 70) – price*). Furthermore, the survey enables to analyze the players' tendency for intuition and analysis, meaning that it will be known and observed how people ended up to a certain price, and whether they made profits or losses. From a statistical point of view, it will be observed whether there seems to be divergence among the more analytical and/or intuitive approaches when it comes to the performance. Ultimately, in the light of the data, it will be concluded whether intuition or analysis seems to have a bigger role in the decision-making processes and what role does AI seem to play in that process respectively.

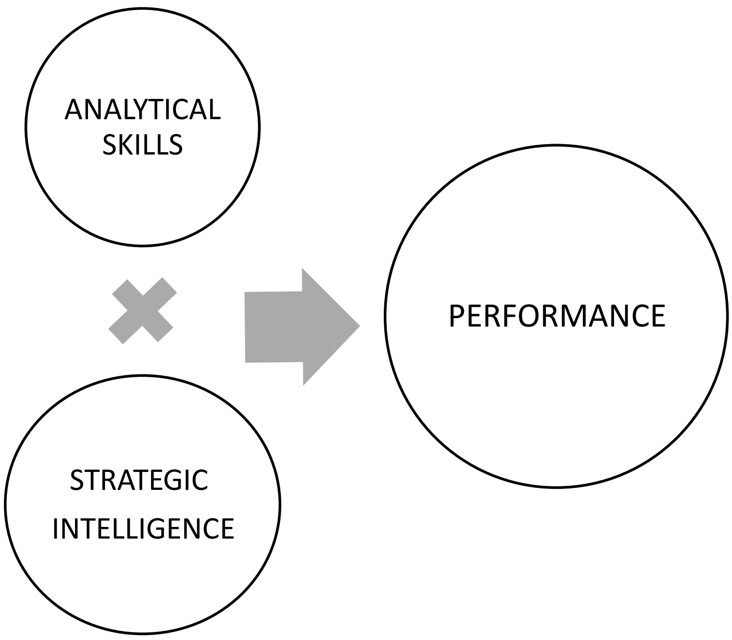


Figure 1. The theoretical model. Hypothesized relationships of analytic skills, strategic intelligence and performance.

3.2.1 Performance

The performance in this model is assessed through the profits that a host manages to make, given that s/he manages to rent his/her apartment. The variables determining the ultimate performance are those of customer value and the profits made, which will be later discussed through a constrained optimization problem in chapter six.

The game part of the experiment consists of two diverse scenarios: the one that randomly allocates the given instructions to the players, which enables different approaches to the provided data (intuitive, analytical, the combination of both and no instructions but overall only humans making decisions in this scenario) and the other one that either includes AI-powered tools in the price determination phase or not (three different scenarios: no AI, augmented price determination process or automated price-setting). More specifically, the analytical skills and the strategic intelligence are measurable separately according to the design of the experimental survey/game and the nature of the statements therein (see appendix 4).

Although there are some inherent biases in surveys and simplified game settings like this, nonetheless the experimental setting has enabled simultaneous analysis of individual actions and skills and the ultimate assessment of the collective, aggregate effect on the market. The role of cognition is considered varying and being a dependent variable of the competitiveness of markets (Levine *et al.*, 2017). Finally, the performance of the experiment's respondents has been incentivized by an economical price, implying that the respondents' choices are affected and pressured by the fact if they will perform well enough they can win the economical prize. This is the so-called induced-value theory (Levine *et al.*, 2017). Ultimately, by being able to analyze the performance of the respondents and their reasoning (provided by their comments and survey responses), conclusions can be drawn on the degree and importance of analytical skills and strategic intelligence for success in P2P house rental contexts such as Airbnb.

3.2.2 Analytical Skills

Analytical skills are considered important by having a role in detailed information processing whereas another set of complementary skills (those of strategic intelligence) are needed to enable people to reason and monitor the wider context and the 'big picture' in a more holistic way. By combining these two sets of skills (known as the dual-system) the risks associated with overreliance on instinct or analysis can be minimized (Hodgkinson & Sadler-Smith, 2018). In this respect, the cognitive reflection test, the need for cognition, and financial literacy are used as tools to measure analytical and intuitive thinking and reasoning.

In the experiment studied in this thesis, analytical skills are measured and assessed through a self-reporting part, among others, where the respondents have to self-declare on a scale from strongly disagreeing to strongly agreeing how they feel about several statements that measure the tendency of the respondents to opt for more intuitive and/or analytical thinking. Additionally, in the game part of the experiment players might be encouraged to exercise more analytical and/or intuitive thinking when approaching the price determination issue. The exact scenario that a player faces is randomly allocated.

Next, each of the components of analytical skills, as considered in this thesis, is gone through in more detail to better understand people's approach and inclination towards certain kinds of reasoning patterns, independently from any technological aid. The statements of the survey measuring and assessing respondents' tendency on these aspects can be found in appendix 4.

Cognitive reflection

One dimension of analytical skills is cognitive reflection. It is defined as a direct measure of a person's ability to reason. Furthermore, two types of cognitive processes can be distinguished according to Shane: one which requires a minimal amount of conscious deliberation and another that is a process requiring slower, more reflective behavior. Moreover, a correlation between patience and cognitive abilities is found (Shane, 2005). Consequently, it is interesting to ask in the light of this definition whether cognitive reflection is then just another synonym for IQ. Also, it is thought-provoking to later see from the results whether those who are more patient by their nature perform better in tasks that require such behavior. Take for instance the study conducted by Shane (2005), demonstrating how '*being smart makes women patient and makes men take more risks*' (Shane, 2005, p.38). Whether there seem to be significantly more risky answers [extreme outliers] among men will be analyzed later in this study once the data will be laid out and visualized (appendices 1 to 3). However, in this respect, it should also be noted that some studies are indicating exactly the opposite when it comes to gender as the difference-making factor in performance. It is found by Nelson (2018) that there are no notable differences in the risk-aversion and performance of the different genders (Nelson, 2018).

Be as it may, cognitive reflection is often additionally linked to the wider concept of intuition that is something to be considered as a nonconscious process (Frith & Singer, 2008). In strategic settings, intuition has a significant but implicit role since it underlines the formation of habits and routines, conscious deliberation, mindfulness, and behavioral strategies as elaborated by Levine *et al*. (2017, p.2405). Often though, it is considered that involving emotions and intuition in the economic reasoning process and decision-making is bad but as Frith and Singer (2008) demonstrate, this is not necessarily so (Frith & Singer, 2008). Whether this can be confirmed also in the case of price determination in P2P contexts will be seen once the data collected will be analyzed later in this study.

In any case, when it comes to the more specific definition of intuition, it is often conceptualized as a method of deciding that is based on fast, non-conscious recognition of patterns and further association of those patterns, leading ultimately to judgment making. The difference between rational, purely analytical reasoning and decision-making, therefore, lays in the speed of processing information and the linearity and logicality of reasoning. Rational decision-making can always be reconstructed and explained afterward whereas in the case of intuition it is often unclear how the decision-maker came to that one particular conclusion. Furthermore, it is observed that generally speaking there tends to be a tension between rational reasoning and intuitive decision-making, meaning these could not be really conjoined. This implies that a rational decision-maker cannot easily accommodate intuitive thinking and vice versa (Calabretta *et al*., 2017, p.366). Table 1, built by Hodgkinson and Sadler-Smith (2018, p.476), illustrates well the distinction between conscious and nonconscious information processing.

Nonconscious information processing	Conscious information processing
Automatic processing	Controlled processing
Heuristic	Systematic
Implicit inferences	Explicit inferences
Heuristic processing	Analytical processing
Implicit/tacit	Explicit
Experiential	Rational
Associative	Rule-based
Intuitive cognition	Analytic cognition
Tacit thought processes	Explicit thought processes
Automatic	Intentional
System 1 (TASS)	System 2 (analytic)
Holistic	Analytic
Impulsive	Reflective
Reflexive (X-system)	Reflective (C-system)
Unconscious	Conscious
Old mind	New mind

Table 1. Nonconscious vs. Conscious Information Processing

Financial literacy

Another dimension of the analytical skills concept is financial literacy – which may be better known as financial knowledge. Typically, the term is used to indicate a need for financial education, and to explain differences and variations in financial outcomes and behavior such as investing and saving (Huston, 2010, p.296-297). Though, it should be noted that there is no consensus or understanding of the concept, which complicates the assessment and generalization of the experiment's results (Huston, 2010). Nonetheless, by being a component of the wider concept of analytical skills, financial literacy is indirectly measured in this thesis, and in the experiment, by assessing the relative performance of those who are overall more analytical in their reasoning.

Need for cognition

Another concept defining the concept of analytical skills for this thesis is the need for cognition. Generally speaking, it is a concept often used in social psychology, measuring self-reported interest towards tasks that are more or less abstract and (may) need logical thinking and reasoning to be solved. In other words, an individual tends to engage in and enjoy pure thinking. It is a desire and need to structure situations and things in meaningful, integrated ways (Cacioppo & Petty, 1982; Lins de Holanda Coelho *et al.*, 2020). The assessment of one's need for cognition is generally done through the '*Need for Cognition Scale*', developed by Cacioppo and Petty (2013). A similar scale and questions are used in the experimental part of this survey to measure respondents' need for cognition.

3.2.3 Strategic Intelligence

Another component enabling the analysis of the performance as defined in this thesis is the concept of strategic intelligence. In general terms, strategic intelligence is often described as the collection, analysis, and dissemination of information with high strategic relevance (Kuosa, 2011, p.458). What this means in practice and competitive situations is that people are required to be able to anticipate what the competitors will and would rationally do. A common method for measuring strategic intelligence is through the so-called guessing game that was developed to assess players' ability to strategize their space and time (Levine, 2017, p.2397). Though, the concept resembles a lot of the one dimension of analytical skills: intuition. This is especially so if strategic intelligence is considered as the cumulation of expertise and knowledge in a specific type of setting, which implies that expertise and experience are vital for intuitive processing and reasoning in the field (Levine, 2017).

Respectively, in the experiment conducted for this thesis, the respondents' ability to take into account the context where they are operating is measured and assessed from the price they ultimately decide to set for their lodgings. The players are provided with information and data on the previous reviews, prices, and effectuated bookings as well as on the comments from successful hosts. Altogether, this information enables the players to be strategic in their reasoning and decisions if they so prefer. The players play two rounds in the game (the first one being a trial round, which is not counted towards the ultimate performance). After the first round, they will be provided feedback on the fact if they managed to successfully rent the apartment or not. This enables the players to assess their strategies of the first round and adjust accordingly for the second consecutive round if they see it important. At the end of the game, the respondents will also comment on the methodology they used for the price determination so it can be further observed from the comments whether they identify the pattern and skills, which led to their final decision.

As will be demonstrated, strategic intelligence is something that varies among individuals and seems to be more like a characteristic that is at least partly developed over time. Though, the strategic nature of the *HomeRent.Com* –game is obvious, especially when the real economic incentive is taken into account. The respondents are incentivized through the possibility of winning 100€ in cash, meaning that the previously mentioned induced value theory applies: people tend to be more considerate and strategic in their actions when they are incentivized with money (Levine *et al*., 2017, p.2401).

Finally, in this respect, one should not conclude on the definition without mentioning game theory and especially dominance solvable games. Generally speaking, what this means is that if a player is rational and believes that so are his competitors, then the most unlikely strategies and prices can and should be iterated (Sedkaoui & Khelfaoui, 2020). Thus, in the case of the experiment done for this thesis, the results of the best performing players should reflect rationality. This is to say that there should not be extreme prices (extremely high or low outliers) that vary too much from the average. Whether this is the case though will be seen once the survey/game results will be analyzed.

3.3 The Hypotheses

The hypotheses in this thesis have been drafted based on the theoretical implications presented in the preceding chapters. They are divided between those referring to the first experiment that studies solely the human reasoning processes (noted with 'a'), and those referring to the second one that measures the impact of AI in the reasoning processes (noted with 'b').

That being said, since it is studied how different, specific reasoning approaches may affect performance, the first null hypothesis takes logically the stand that there is no single way for successful decision-making but all approaches are equally likely to lead to good outcomes. Therefore, the first null one is as follow:

> *H0a: There is no single way to conduct a human reasoning process to succeed. Intuitive or analytical approaches are both as likely to lead to the highest performance.*

Though, it can be reasoned that in the absence of one single way for reasoning it would be most likely to obtain the best results if one practices equally analytical and strategic reasoning in the price determination process. Obviously, this is not so much a conscious decision that one can make but rather dependent on the particular individual in question (Calabretta *et al*., 2017). Consequently, the following is argued in the first alternative hypothesis on the experiment one:

> H1a: *Combining intuitive and analytical reasoning leads to the highest performance.*

Additionally, it is examined whether gender can be considered as a sort of predictor for platform success. However, this assumption is found to be somewhat controversial since it seems that there is no clear consensus whether gender indeed affects risk-taking and that way decision-making and performance (Nelson, 2018; Shane, 2005). Be as it may, it is nonetheless investigated in this study whether in the collected dataset there appears to be variation among the gender groups. Therefore, the second alternative hypothesis is the following:

> H2a: *There is a clear difference between the different gender groups in terms of performance.*

In respect to the second experiment, and derived from the argumentation of this thesis, as a null hypothesis it is considered that there is no difference between types that have relied on AI and those who have not. Therefore, the null one for the second experiment is the following:

> H0b*: Involvement of AI does not significantly affect performance. No notable variation between the three types can be detected.*

However, if it is considered that humans are inherently biased and subjective in their reasoning (Einhorn, 2021; Lindebaum, D., *et al*., 2020), then the following can be argued in the first alternative hypothesis of experiment two:

> *H1b: Use of AI in decision-making improves performance. To rely on AI in reasoning is better than a reasoning process merely conducted by a human.*

Nevertheless, as much as it is reasonable to augment the human reasoning processes with technology, it is desirable to maintain a certain level of human input in the process as well (Frank *et al*., 2017). Therefore, it is considered and tested in the second alternative hypothesis on the second experiment whether humans tend to perform better in cases where AI is augmenting the human mind rather than entirely replacing it. The hypothesis is as follow:

> *H2b: The use of AI to augment a reasoning process improves the performance, meaning augmentation outperforms automation in a reasoning process.*

To sum up the above-said in a more theoretical form, the hypotheses that have been drafted can be alternatively expressed as follow:

The Main Hypotheses for the Experiment I

H0a: $\mu1 = \mu2 = \mu3 = \mu4$

H1a: The mean of the comparison group 3 is different and higher from those of the other comparison groups.

H2a: The mean of the other gender group [male or female] is consistently higher over that of another.

The Main Hypotheses for the Experiment II

H0b: $\mu1 = \mu2 = \mu3$

H1b: The means of comparison groups 2 and 3 [the types] are different and higher from that of comparison group 1.

H2b: The mean of comparison group 2 is higher than that of the comparison groups 1 and 3.

4. Experimental Design; Data and Methodology

There is a close relationship between the design of an experiment and the statistical analysis conducted on the collected data. A successful experimental study should be able to manipulate the constant variables in a way that allows concluding whether a change of variables is a cause of the manipulation (Ross & Morrison, 2003). This is precisely what this thesis aims at doing: studying the (non)existing interactions among the independent variables of gender and type, and eventually conclude whether price, profits, or customer value are dependent on the manipulations made on the independent variables. In other words, the study of this thesis is an experimental one, referring to a scientific approach using two sets of variables as referred above (Ross & Morrison, 2003). The hypotheses drawn for the analysis of this study are supported by the theoretical resources presented in chapter three. Altogether, this thesis conducts a quantitative analysis of the survey research.

Overall, the survey/game was conducted by 154 persons of which 79 females and 74 men. Experiment one was allocated to 39 males and 46 females whereas experiment two was conducted by 35 males and 33 females. The average age of the respondents was 21,3 and the majority of them, 104 persons precisely, were from Italy. Additionally, the average length of tenure among the respondents has been 0,5 that is less than one year. The experiment has been conducted anonymously, meaning the respondents are not known. The distribution of the invitations to take part in the experiment has happened by exploiting various (social media) networks.

4.1 Data Collection

The survey/game that is the target of the analysis conducted in this thesis has consisted of two parts as explained before (the self-assessment and the game). Though the primary interest of this thesis is on the game part and the second round of it more precisely (the first one being a trial round). Additionally, it should be noted that more data than discussed in this study has been collected but since the available time and space for this paper have imposed some limitations, only a few variables and parts of the data are addressed here. The self-assessment part of the survey is mainly just referred to when the best and worst-performing players are assessed. The statements of the survey can be found in appendix 5 where they are roughly divided according to the *analytical skills – strategic intelligence* division as made in the theoretical model.

4.1.1 The HomeRent.Com -Game

The second part of the experiment is the decision-making game where the participants are incentivized by the possibility to win 100€ in cash if they rank in the top three with their performance i.e. they manage to get the highest profits while getting their apartment rented. Essentially, the task of the players is to decide the number of amenities they decide to offer with the short-stay rental property that they are renting through the platform. Additionally, they will need to determine the price in a manner they consider the most reasonable in the light of the competition and the value that the function of the price and amenities is producing for the potential customers, save for situations where the price has been determined automatically by AI (experiment 2, scenario 3). The market setting in the game is largely simplified: there are neither seasonality nor Covid-19 influences. Also, it should be noted that *HomeRent Inc*. is a fictional platform – an online marketplace offering lodgings and tourism experiences operating solely as a broker between the apartment owners/event organizer and potential customers. It is a platform resembling Airbnb.

In the beginning, once the players start the game they are asked to confirm that they have understood the rules of the game after which they will decide on a nickname and provide their email address. Nonetheless, the survey/game is anonymous and the participants are not identifiable apart from their age, nationality, email address, and years of working experience. No information is disclosed to the other participants about a player so the players do not know with whom they are competing.

Secondly, after all the formalities, it is clearly stated that the purpose of the player is to maximize his/her profits in the game. S/he is provided with pictures of the apartment, the cost of the amenities, and the profit formula as well as the formula for counting the induced value for customers are given, which are the following:

$$\text{Profits} = \text{Price} - (\text{Number of Amenities} \times €20)$$

$$\text{Value for Customer} = (\text{Amenities} \times 70) - \text{Price}$$

The winner is ultimately the person who manages to obtain the highest profits, given s/he manages to rent his/her apartment.

The hosts are provided with the past year's review score, the average price, and the average number of amenities they offered. Also, the day-to-day data on these variables from last month is disclosed and whether the apartment got booked or not. The customers decide whether to book the apartment based on two criteria only: the price and the number of amenities offered. The apartment that in the end produces the highest value for customers is booked. Finally, it is mentioned that the demand is lower than the supply thus making the setting a competitive one. After determining the number of amenities and the precise price, the players will know whether they have managed to rent the apartment or not (the trial round). Then they will move to the second (actual) round. In the second round, the players will encounter different scenarios, randomly allocated by the computer, which are the following:

- Experiment I; Studying Human Decision-making:
    1. Intuitive approach encouraged;
    2. Analytical approach encouraged;
    3. Combination of both supported;
    4. No specific guidelines are given.

- Experiment II; Decision-making with AI
    1. Reasoning without any help from AI;
    2. Automated price determination;
    3. Augmented price determination process.

Finally, the players are asked to indicate on a scale from *'not at all'* to *'extremely'* how much the different pieces of information given to them affected their decision-making process. It is this information that enables the later, holistic analysis of the best-performing players. In the end, the players are additionally asked to indicate their gender, age, country of origin, and years of working experience.

4.2 Data Analysis

Even though the sample size (i.e. the number of respondents in the survey/game) has enabled the analysis and discussion of the data, it should be nonetheless noted that it has still been quite small and heterogeneous in terms of age, tenure, and country of the respondents. For these reasons, it has not been possible to meaningfully analyze the differences between the various age, country, or tenure groups since there has not been much variation on them. Initially, the purpose was indeed to consider these variables and assess the impact of demographics on the performance but as said, in this case, this would not have been a fruitful study.

Be as it may, the Kruskal-Wallis test has been chosen for the data analysis in this thesis, and the variables that are of interest are: i) the *type* of the experiment (within the first or second experiment) that the players encounter in the game and, ii) *gender*. These are considered independent variables. Respectively, price, profits, and customer value are treated as dependent ones since these ultimately enable the analysis of performance. Overall, the Kruskal-Wallis test has been exploited as the main way to analyze the data since the data is non-parametric, as will become apparent in the following chapters. Subsequently, the statistically significant results are further analyzed through the applicable post hoc tests.

The alpha level i.e. the significance level in the performed statistical tests of this thesis has chosen to be the standard .05 (Turner & Thayer, 2001). In other words, a particular result is considered statistically significant only, and leading to rejection of the null hypothesis, in cases where the p-value is less than .05. It follows that the confidence interval is then 95%. In other words, in this thesis, it is considered that if the same experiment were to be run 100 times, only in 5 cases it would be possible to reject the null hypotheses and confirm the alternative ones. Though, as will become apparent, the obtained p-values that are less than the significance level in this thesis are primarily all less than .01, meaning that it could have been possible to use .01 as the overall alpha level and that way reduce the risk of false-positive results and prevent even more the type I error from occurring. However, a decision has been made to stick to the status quo (i.e. .05) since the inherent risks of that in comparison to the .01 level are not so weighty.

Overall, the data analysis has been carried out by first following a set research plan but due to violated assumptions for the ANOVA, the plan was forced to be modified. Initially, the purpose was to rely solely on two-way ANOVA but after seeing the data and its strong heterogeneity in terms of age, tenure, and nationalities the tests had to be changed. Additionally, as was mentioned, the data is non-parametric meaning that ANOVA would not have been the most reliable in terms of the results since in general it is meant for parametrically distributed data. Eventually, the Kruskal-Wallis test was chosen as an alternative for ANOVA since it does not require homogeneity of variances on the tested groups. Overall, it is considered more robust on violations of normality than ANOVA (Rivera, 2020). Additionally, after running the mentioned tests, applicable post hoc tests were performed to find out precisely which groups are different from the others since the main tests tell solely whether there are differences within the groups but they say nothing on the differences between them. Consequently, Dunn's test was applied with Bonferroni adjustment. The purpose of the Bonferroni adjustment is to protect from the Type I error (Investopedia, Bonferroni Test).

All of the tests have been run on the RStudio software, meaning that no complex computations have been made manually, which could have increased the risk of error. Finally, after obtaining the statistical results, a constrained optimization problem was built to model one possible approach to the winner determination on the game. A function was built from the equations provided in the game for customer value and profits. Additionally, the information provided in the game was exploited to determine the lowest customer value that a host should provide to get his/her apartment rented. Ultimately, this was followed by a manual assessment of the best and worst-performing players and their respective self-assessment and written comments. Altogether, these different pieces of analysis have enabled a holistic discussion and reasoning on the collected data, leading to conclusions that at least partly support the hypotheses made in the light of the theoretical background presented earlier in this paper.

4.3 Validity and Reliability

By assessing the validity of the conducted study, it is referred to the degree to which the obtained results represent the variables they are supposed to. By reliability instead, consistency of the defined measures is meant (here the theoretical model and its components) (Price, *et al.*, 2015). In this study, the overall method has been applied to fit the research and thus the results can more or less be considered valid and reliable. First, the data collection has happened through statically correct methods, namely through the survey/game. Secondly, the studying of the relevant theoretical background, followed by trial and error on the statistical tests have led to conclusions that support each other and confirm the theoretical starting points even if not all the null hypotheses are eventually rejected. Altogether, following the precise steps for the statistical tests and conducting the computations on RStudio, the validity and reliability of the conclusions have been maximized and guaranteed. No theoretical claim or argument has been made without support from another, recognized source.

4.4 Ethical Aspects and Method Discussion

The research on this thesis can be considered fully objective. The author is impartial what comes to the experiment's design, data collection, followed analysis, and the ultimate conclusions. For these reasons, understandably several challenges have emerged along the way, which have affected the ultimate design, analyses, and discussion. Consequently, few points on the carried research should be made:

First, as has been elaborated, the sample has ultimately been quite homogeneous in terms of age, nationality, and tenure, which caused the abandonment of the plan to observe the (combined) effects of age, tenure, and nationality on the performance. All in all, a wider background data gathering could have potentially given more support, depth, and insights for the obtained results. However, delimitations have been compelled to make, thus restricting the array of data that has been taken into account for this thesis. For instance, it could have been additionally studied what the amount of time that people spend on each question and task indicates. Also, only a little attention has been given to the survey part of the experiment. A much more insightful would have been to assess each answer made in the game with the self-assessment done in the survey part and take the time spent on these into account. Be as it may, the delimitations had to be drawn somewhere, giving rise to subsequent studies on the subject.

5. Kruskal-Wallis Test

In this chapter, the statistical tests which have been performed will be demonstrated: First, the summary statistics will be presented, followed by the Kruskal-Wallis test, and the applicable post hoc tests. The precise test has been chosen based on the drafted hypotheses, and the characteristics that the dataset has shown. This is to say, first, that since the data was found out to be not normally distributed (appendix 1), a non-parametrical test such as the Kruskal one had to be chosen. Secondly, the nature of the drafted hypotheses indicated towards a test that would enable comparison between more than two groups of the independent variables in respect to the dependent ones. Additionally, the chosen test is optimal for randomized experiments such as the one studied in this thesis. Generally speaking, the Kruskal-Wallis test is a non-parametric alternative for ANOVA (Rivera, 2020). By performing the Kruskal test, it is possible to observe whether there seem to be significant differences among the dependent variables when grouped by either gender or the type of experiment. The statistical tests and analyses of this thesis have been conducted through the RStudio software that is an open-source platform for statistical computations.[1] For that reason, the applicable statistical theory, computations, and the corresponding formulas will not be discussed in depth in this thesis for the sake of preventing the length of the thesis from expanding too much. The precise code that has been used for these computations can be found in appendix 5.

Summary Statistics

In the following tables, the collected data has been laid out as summary statistics, grouped by the different types of the randomized experiment and gender. The tables present the entirety of the data that has been used as an input for all the different statistical tests and analyses performed in this thesis.

[1] http://rstudio.com

	TYPE	VARIABLE	N	MEAN	SD
EXP.1.	1	PRICE	22	267	27,3
	2	PRICE	14	296	89,5
	3	PRICE	32	239	46,5
	4	PRICE	17	241	74,2
EXP.2.	1	PRICE2	23	246	56,9
	2	PRICE2	31	214	68,7
	3	PRICE2	15	300	0
	TYPE	VARIABLE	N	MEAN	SD
EXP.1.	1	PROFIT	22	153	31,1
	2	PROFIT	14	166	83,8
	3	PROFIT	32	132	46,1
	4	PROFIT	17	124	67,4
EXP.2.	1	PROFIT2	23	142	59,2
	2	PROFIT2	31	99,8	76,2
	3	PROFIT2	15	188	12,6
	TYPE	VARIABLE	N	MEAN	SD
EXP.1.	1	CV	22	131	63,1
	2	CV	14	159	84,4
	3	CV	32	137	71,6
	4	CV	17	171	68,6
EXP.2.	1	CV2	23	119	81,9
	2	CV2	31	186	109
	3	CV2	15	92	44,3

Table 2. Summary Statistics Grouped by Type.

	GENDER	VARIABLE	N	MEAN	SD
EXP.1.	FEMALE	PRICE	46	234	45,2
	MALE	PRICE	39	282	67,5
EXP.2.	MALE	PRICE2	34	241	64
	FEMALE	PRICE2	35	246	66,9
	GENDER	VARIABLE	N	MEAN	SD
EXP.1.	FEMALE	PROFIT	46	125	45,4
	MALE	PROFIT	39	161	62,8
EXP.2.	MALE	PROFIT2	35	132	70,5
	FEMALE	PROFIT2	34	134	70,9
	GENDER	VARIABLE	N	MEAN	SD
EXP.1.	FEMALE	CV	46	149	72
	MALE	CV	39	142	71,8
EXP.2.	MALE	CV2	35	141	99,5
	FEMALE	CV2	34	145	95,8

Table 3. Summary Statistics Grouped by Gender .

The test has been run with the RStudio, allowing to measure the effect size through the squared eta that measures and observes the variance in percentiles in the dependent variables as explained by the independent ones (Ellis, 2010). Subsequently, to better analyze the differences between the groups, the multiple pairwise comparisons and Dunn's post hoc test have been performed to determine which groups, if any, are the ones that differ. The results are reported in the following sections and the applicable graphs plotted on the data can be found in appendices 2 and 3.

Computations

K-W BY GENDER		PRICE	PROFIT	CV
EXP.1.	n	85	85	85
	statistic	9,69	7,22	0,647
	df	1	1	1
	p-value	0,000185	0,000721	0,421
EXP.2.	n	85	85	85
	statistic	0,0197	0,000146	0,0527
	df	1	1	1
	p-value	0,888	0,99	0,818

Table 4. Kruskal-Wallis Test by Gender.

K-W BY TYPE		PRICE	PROFIT	CV
EXP.1.	n	85	85	85
	statistic	8,06	5,43	4,02
	df	3	3	3
	p-value	0,0448	0,143	0,143
EXP.2.	n	85	85	85
	statistic	29	25,8	8,77
	df	2	2	2
	p-value	4,92E-07	2,56E-06	0,0125

Table 5. Kruskal-Wallis Test by Type.

Effect size

In addition to the p-values indicating the statistical significance of the results, the respective effect sizes are computed in this section. More specifically, the p-values can be considered as indicators telling whether certain variables have an impact on the results whereas the effect size indicates the magnitude of difference between the different group means (Frank, 2020; Ellis, 2010). In short, effect size allows determining the level of impact of the independent variables on the dependent ones. The eta squared is used here to measure the effect size, which is computed as *(H-k+1)/(n-k)*. The *H* in the formula refers to the value obtained in the Kruskal test, *k* refers to the amount of the groups and *n* is the number of the observations. It is noted by Tomczak, (2014) that by convention the values are interpreted in the following manner: .01 -

< .06 (small effect), .06 - < .14 (moderate effect), >= .14 (large effect) (Tomczak & Tomczak, 2014; Ellis, 2010, p.15). The results are the following:

EFFECT SIZE BY TYPE		PRICE	PROFIT	CV
EXP.1.	n	85	85	85
	Effect size	0,0624	0,0299	0,0126
	Magnitude	moderate	small	small
EXP.2.	n	85	85	85
	Effect size	0,330	0,290	0,0826
	Magnitude	large	large	moderate

Table 6. Effect Size by Type.

EFFECT SIZE BY GENDER		PRICE	PROFIT	CV
EXP.1.	n	85	85	85
	Effect size	0,105	0,0749	-0,00426
	Magnitude	moderate	moderate	small
EXP.2.	n	85	85	85
	Effect size	-0,0118	-0,012	-0,0114
	Magnitude	small	small	small

Table 7. Effect Size by Gender.

Consequently, it can be observed from the results how in experiment two, grouped by type, the type has a large impact on the results as a whole. Instead, gender does not seem to have a real impact in the second experiment but it seems to play a moderate role in the case of the first one. Altogether, these results seem to support at least partly the claims and hypotheses made in this thesis; gender seems to have an impact when pure human decision-making is concerned but this effect diminishes once the AI is relied on in the reasoning process. In addition, AI seems to strengthen the performance and particularly one form of it, which will be addressed and discussed later in this study.

Multiple Pairwise Comparisons with Dunn's Test

To conclude with precision which are the groups that differ, a pairwise comparison is done by exploiting Dunn's test. The test is one possible post hoc test after the Kruskal-Wallis test, which is to say it fits for non-parametric data. It functions by dividing the significance level by the number of comparisons (Tomczak & Tomczak, 2014; Ellis, 2010).

The results demonstrate the pattern that has already appeared consistently in this study; the principal differences are between the means of price and profits in experiment two when grouped by type and between the gender groups in experiment one. Logically, the automated price as set in type 3, in experiment two, explains this partly but it is interesting to observe how also the profits are generally speaking different. Instead, in the setting where only human reasoning is used (the experiment one) there is a difference between the gender groups in the prices set and profits obtained. The results are reported in the following tables. The adjusted p-value is the one that is taken into consideration. In case the adjusted p-value equals one, this indicates that there is no evidence to reject the null hypothesis (Turner & Thayer, 2001; Frank, 2020; Riviera, 2020).

DUNN'S TEST BY GENDER	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	PRICE	Female	Male	46	39	3,11	0,00185	0,00185	**
EXP.2.	PRICE 2	Female	Male	34	35	-0,14	0,888	0,888	
DUNN'S TEST BY GENDER	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	PROFIT	Female	Male	46	39	2,69	0,00721	0,00721	**
EXP.2.	PROFIT 2	Female	Male	34	35	0,0121	0,99	0,99	
DUNN'S TEST BY GENDER	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	CV	Female	Male	46	39	-0,804	0,421	0,421	
EXP.2.	CV 2	Female	Male	34	35	-0,229	0,818	0,818	

Table 8. Dunn's Test by Gender.

DUNN'S TEST BY TYPE	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	PRICE	1	2	22	14	0,221	0,825	1	
	PRICE	1	3	22	32	-2,18	0,0291	0,175	
	PRICE	1	4	22	17	-1,75	0,0794	0,476	
	PRICE	2	3	14	32	-2,12	0,0338	0,203	
	PRICE	2	4	14	17	-1,78	0,0752	0,451	
	PRICE	3	4	32	17	0,126	0,9	1	
EXP.2.	PRICE 2	1	2	23	31	-2,02	0,0433	0,13	
	PRICE 2	1	3	23	15	3,43	0,0006	0,0018	**
	PRICE 2	2	3	31	15	5,39	7,06E-08	2,12E-07	****
DUNN'S TEST BY TYPE	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	PROFIT	1	2	22	14	0,0401	0,968	1	
	PROFIT	1	3	22	32	-1,36	0,174	1	
	PROFIT	1	4	22	17	-1,98	0,0474	0,284	
	PROFIT	2	3	14	32	-1,22	0,223	1	
	PROFIT	2	4	14	17	-1,81	0,07	0,42	
	PROFIT	3	4	32	17	-0,878	0,38	1	
EXP.2.	PROFIT 2	1	2	23	31	-2,36	0,0182	0,0545	
	PROFIT 2	1	3	23	15	2,83	0,00472	0,0142	*
	PROFIT 2	2	3	31	15	5,05	4,46E-07	0,00000134	****
DUNN'S TEST BY TYPE	VARIABLE	GROUP 1	GROUP 2	n1	n2	STATISTIC	P	P.ADJ.	P.ADJ.SIGNIF.
EXP.1.	CV	1	2	22	14	0,947	0,344	1	
	CV	1	3	22	32	0,481	0,631	1	
	CV	1	4	22	17	1,88	0,0595	0,357	
	CV	2	3	14	32	-0,595	0,552	1	
	CV	2	4	14	17	0,789	0,43	1	
	CV	3	4	32	17	1,58	0,113	0,68	
EXP.2.	CV 2	1	2	23	31	2,03	0,0427	0,128	
	CV 2	1	3	23	15	-0,934	0,35	1	
	CV 2	2	3	31	15	-2,76	0,00579	0,0174	*

Table 9. Dunn's Test by Type.

Report

The conducted Kruskal-Wallis Test showed some statistically significant differences between the independent variable groups. In experiment one, there were significant differences in price between types (p=0,0448), and also significant differences were found in price (p=0,000185) and profits (p=0,00000256), when grouped by gender in experiment one. In the second experiment, significant differences were found in all the dependent variables when grouped by type (price p= 0,000000492; profit= 0,00000256; CV=0,0125) but none when grouped by gender.

Secondly, the effect size of the Kruskal-Wallis test was measured. The eta squared was used as the indicator of the effect on the differences. The results showed the percentage of variance in price, profit, and customer value (the dependent variables), which are explainable by the independent variables (here either type or gender). The results demonstrated a large effect in price (efs=0,330) and profits (efs=0,290) when grouped by type in experiment two. Moderate effects, among others, were reported in price (efs=0,0624) and profits (efs=0,0299) in experiment one when grouped by gender. The categorization of the values into small, moderate or large effect has been done in line with the standard that appears in the published literature, these being .01 - < .06 (small effect), .06 - < .14 (moderate effect), >= .14 (large effect) (Tomczak & Tomczak, 2014; Ellis, 2010).

Finally, the Dunn's test was performed to assess and identify which groups precisely differed significantly. This was done by comparing the different types and genders in pairs, on the dependent variables. From the results, it can be observed that the significant differences were between males and females on price (p=0,00185) and profits (p=0,00721) in experiment one. In the experiment two, statistically significant differences were found in price between the groups 1 and 3 (p=0,0018) and 2 and 3 (p= 0,000000212) but also in profits (p=0,0142 for 1&3; p= 0,00000134 for 2&3). The applicable boxplots visualizing these findings can be found in appendices 3 and 4.

6. Determining the Winners and Losers; A Constrained Optimization Problem

Finally, after running all the applicable tests, it is time to determine the best performing players of the game i.e. those who have managed to rent their apartment and gain the highest profits. Ultimately, the best performing and respectively the worst performing players will be analyzed in more detail. The self-assessment the winners and losers have made will be taken into account, which further enables analyzing whether their characteristics are actually in line with the findings made in the statistical tests. Be as it may, the determination of the winners and losers will be done by building a constrained optimization problem with the information that was provided in the game. However, it should be stressed that the line of reasoning that is presented here is not necessarily the one that is used by computer algorithms to define the ultimate winners. *It has not been disclosed to the author how the actual algorithm works in the game, and for that reason the conclusions drawn here may derive from the actual solution designed for the game.* The adopted approach is thus one possible, theorized approach trying to make sense of the results and rank the participants.

Below is reported the information that was provided for the players in the game. The highlighted cells indicate the lowest customer value that led to a booking.

DAY	PRICE (€)	#AMENITIES	PROFITS	CV	BOOKED	REVIEW SCORE
-1	280	5	180	70	Yes	51,8
-2	260	5	160	90	Yes	55,8
-3	230	4	150	50	Yes	47,8
-4	300	4	220	-20	No	
-5	300	6	180	120	Yes	61,8
-6	290	5	190	60	Yes	49,8
-7	142	2	102	-2	No	
-8	156	2	116	-16	No	
-9	145	5	45	205	Yes	78,7
-10	170	2	130	-30	No	
-11	194	4	114	86	Yes	55
-12	170	4	90	110	Yes	59,8
-13	200	4	120	80	Yes	53,8
-14	270	5	170	80	Yes	53,8
-15	130	5	30	220	Yes	81,8
-16	137	3	77	73	Yes	52,4
-17	128	4	48	152	Yes	68,2
-18	181	7	41	309	Yes	99,6
-19	108	1	88	-38	No	
-20	196	7	56	294	Yes	96,6
-21	159	1	139	-89	No	
-22	109	6	-11	311	Yes	100
-23	171	2	131	-31	No	
-24	200	3	140	10	No	
-25	141	3	81	69	Yes	51,6
-26	197	3	137	13	No	
-27	210	3	150	0	No	
-28	200	4	120	80	Yes	53,8
-29	300	5	200	50	Yes	47,8
-30	280	4	200	0	No	
MIN	108	1	-11	-89		47,8
MAX	300	7	220	311		100

Table 10. Previous Month's Booking Information Provided in the Game.

6.1. A Constrained Optimization Problem

As with the statistical tests performed in this study, the ultimate winners have been determined by building a constrained optimization problem into RStudio that has performed the computations. Technically speaking, the profit and customer value formulas have been provided as the constraints and inputs for RStudio: *profits; price-(#amenities*20)* and customer value; *(#amenities*70)-price*. Additionally, by basing to the information provided in the game on the last month's booking rates, reviews, prices, and the number of amenities, it has been calculated that the lowest customer value that a host has to offer is 50€ to get the apartment rented, which also implies the lowest possible review score of 47,8%. Reversely, the highest price that has led to a booking has been 300€. From that, a constrained optimization problem has been built where it has been sought to maximize the profit function while keeping the customer value as low as possible.

By exploiting the RStudio, a theoretical price of 440€ and an apartment with 7 amenities appears to solve the constrained problem in the most optimal way *when only the customer value is considered*. In other words, this bundle of price and amenities lead to high profits by delivering the lowest possible customer value. However, it can be considered that this is not the most optimal solution when the other constraints of price are taken into account. As said, no apartment with a price higher than 300€ has been rented. Consequently, a constrained optimization problem has been solved through the Simplex algorithm, by solving the following constrained problem where the aim is to maximize the profit equation subject to the customer value equation, with the mentioned restrictions:

$$
\begin{aligned}
&\text{Maximize}: -20x1 + x2 \\
&\text{subject to} \quad 70\,x1 - x2 \geq 50 \\
&x1 \geq 1 \\
&x1 \leq 7 \\
&\qquad x2 \geq 20 \\
&\qquad x2 \leq 300
\end{aligned}
$$

In the problem, the variable x1 refers to the number of amenities and x2 to that of price. As instructed in the game, the maximum number of amenities is 7, which imposes a limit for them in the problem. The variable x2 has respectively been constrained to the maximum price of 300€ and the lowest possible price of 20 without losing money i.e. profits 0€. Consequently, the simplex algorithm solves the problem by setting the price at 300€ with 5 amenities, producing 200€ in profits for the host.

All in all, it can be considered that in practice to end up with a solution like this requires quite a bit of an analytical approach – even if this combination has appeared once in the data set provided in the last month’s booking. It is much more intuitive to consider the average prices and number of amenities when one wants to play as safely as possible.

In this respect it should be borne in mind that in the second experiment under type 3, the price has been set automatically by AI at 300€, thus not giving the players even a chance to reach higher levels of price. In such a case, the imposed price is primarily set in line with the interests of the platform, which is to maximize the customer value function and get as many apartments rented through the platform as possible but still keep the hosts in the platform by providing them enough economic incentives (Van Alstyne *et al.*, 2019). This can be supported by the results obtained from the Kruskal-Wallis test, conducted on the second experiment; the automatically set price increasingly affected the customer value when compared to the augmented involvement of AI or lack of it. Naturally, there are more players with this bundle of price and amenities in the second experiment than in the first one.

6.2. Analysis on the Winners

In this section, the three best performing players are to be assessed, separately for both experiments since as explained in the second experiment under the type 3 (i.e. price automatically set by AI) there has been a roof for the maximum profits that a player could have reached. In the second experiment and under type 3, there have been in total eight different respondents obtaining the highest possible profits under the set price of 300€. However, only a couple of them has been picked for further analysis. The results are the following:

TOP PERFORMERS								
EXPERIMENT 1								
TYPE	PRICE	AMENTITIES	CV	PROFIT	GENDER	AGE	COUNTRY	TENURE
3	300	5	50	200	Male	21	Greece	0
1	300	5	50	200	Female	25	Finland	1
1	300	5	50	200	Male	25	Italy	0
3	300	5	50	200	Female	19	Finland	0
1	300	5	50	200	Male	25	Italy	0

Table 11. Top Performers Experiment 1.

WINNERS' SELF-ASSESSMENT							
Order	['Your profits' equation]	['Value to customer' equation]	[Expert's Advice appeared on screen]	[Yearly averages of price and reviews]	[Reviews and prices of the whole last month]	[Reviews and prices of the last 3 days]	Type
EXPERIMENT 1							
1	Extremely	Considerably	Slighlty	Moderately	Considerably	Considerably	3
2	Moderately	Moderately	Slighlty	Considerably	Extremely	Considerably	1
3	Extremely	Extremely	Not at all	Not at all	Considerably	Not at all	0
4	Extremely	Moderately	Not at all	Moderately	Extremely	Slighlty	0
5	Extremely	Extremely	Not at all	Not at all	Considerably	Not at all	0

Table 12. Winners' Self-Assessment Experiment 1.

Comments:

Experiment 1.

1. Male, 21, Greece, Type 3

The minimum review score that was recorded was 47,8% which corresponds to a value for tenant = 50. With this as a minimum accepted value, running simplex method the max profit is at 300 with price=440 and 7 amenities. However, sellling such an apartment is like trying to sell a Ferrari, which *would bring enormous profit but it is really hard to sell. So I moved to a more friendly proposition that fluctuates around the average values indicated. Furthermore, the most profitable day was the one with the price at 300 and 5 amenities returning 200 profit. Following this example I decided to pick these numbers as well.*

2. Male, 25, Italy, Type 1

I confronted the profits made with the value provider to the customer each day. I found out that the customer won't book my apartment if the value provided was lower than 50. With this in mind I looked for the best combination of amenities and price which gave out the max profit without bringing the customer value below 50. Moreover, I constrained myself with a max price of 300 as I thought that I could not rent my apartment at not competitive prices, even when giving lots of amenities.

By observing the results some interesting, theory-supporting patterns can be recognized: First, the best performing players seem to fall under the types that emphasized the analytical approach to price determination. Secondly, in the first experiment, the strongest impact seems to have been on the provided equations to calculate the profits and customer value. The last month's booking information has also played a strong but varying role in the reasoning process. Captivatingly, the expert advice has not played almost any role at all among the best-performing participants of the first experiment. Furthermore, by observing the free comments of some of the best performing players it can be observed that it has been a strongly analytical approach that these players have taken to the price determination dilemma. Additionally, these players have also realized and emphasized the fact that with the lowest possible customer value and highest profits combination it may be possible to rent the apartment but it will be hard. This was perfectly expressed by one player, a male of 21 years old from Greece: '*selling such an apartment is like trying to sell a Ferrari, which would bring enormous profit but it is really hard to sell'*. Finally, it is interesting to observe how under experiment one none of the best performing players played under the type 2 or 4 of the game, which technically encouraged the players to be purely analytical or nothing at all. However, as is apparent these responses are more or less analytical but with a hint of strategic intelligence since on average you do not 'sell a Ferrari every day'. Thus, an average performance without excessive risks seems to be the way to go, in the first experiment at least.

TOP PERFORMERS								
EXPERIMENT 2								
TYPE	PRICE	AMENTITIES	CV	PROFIT	GENDER	AGE	COUNTRY	TENURE
3	300,00	5,00	50,00	200,00	Female	26	Greece	0
3	300,00	5,00	50,00	200,00	Male	22	Italy	0
1	300,00	5,00	50,00	200,00	Male	21	Italy	3
3	300,00	5,00	50,00	200,00	Female	20	Italy	1
3	300,00	5,00	50,00	200,00	Male	20	Italy	0
3	300,00	5,00	50,00	200,00	Female	21	Italy	0
1	300,00	5,00	50,00	200,00	Female	21	Italy	3

Table 13. Top Performers Experiment 2.

WINNERS' SELF-ASSESSMENT							
Order	['Your profits' equation]	['Value to customer' equation]	[Expert's Advice appeared on screen]	[Yearly averages of price and reviews]	[Reviews and prices of the whole last month]	[Reviews and prices of the last 3 days]	Type
EXPERIMENT 2							
1	Extremely	Extremely	Slighlty	Slighlty	Considerably	Not at all	3
2	Considerably	Moderately	Not at all	Considerably	Extremely	Slighlty	3
3	Moderately	Moderately	Moderately	Moderately	Considerably	Considerably	3
4	Considerably	Considerably	Not at all	Not at all	Considerably	Not at all	1
5	Moderately	Extremely	Slighlty	Slighlty	Considerably	Slighlty	3
6	Considerably	Considerably	Not at all	Not at all	Considerably	Not at all	3
7	Extremely	Extremely	Considerably	Considerably	Moderately	Slighlty	3

Table 14. Winners' Self-Assessment 2.

Comments:

<u>Experiment 2.</u>

1. Female, 26, Greece, Type 3

Calculating my profit and the costumer's profit for each day.
*From experience I thought I need more than 50% profit than cost would be ok.. (for 6 facilities 6*20=120 so more than 240 total costs).*
I saw on the table that customers never have been happy with less than 3 facilities, i didn t need more than 6 to have a happy customer. I
In both cases... I had more than my previous average profit, customers had more than their average profit..
I think I could ask even more for one night..!

2. Male, 22, Italy, Type 3

In the first round, I tried to combine my intuition with the provided data. Considering the cost of each amenity and subtracting (20x5) to the price. Then, as this would have been the price to guarantee me to rent, I decided to add on top a margin of 30% (estimate) to balance the risk of not renting and the expected profit coming from it.

3. Male 21, Italy, Type 1

Intuition.

Instead, in the second experiment, there seems to be more variation on the weighting of the different factors by the players. Additionally, it is noteworthy that none of the listed players come from type 2 in the second experiment, which was the scenario of the game where the reasoning process has been augmented by AI. Moreover, when it comes to the comments of the players who had provided them, a more intuitive approach than in the case of the first experiment can be read from them. Though, logically the involvement of AI has played a major role in the performance of the players, which is to say that more guidance has been in place in the first place.

Overall, regardless of the experiment, the players identified here have all more or less adopted an analytical approach to reasoning and price determination. Consequently, what this may imply is that it is the analytical approach that prevails in such a short-term apartment rental context when the price determination is concerned. Though, what can be interpreted from the responses and comments is a certain level of risk-aversion: there is no point in excessive risk-taking for better profits. Better an average performance every day than a great one every once in a while. In theory, the price of 440 with 7 amenities could be a great choice but in practice, this may be too risky also because the dynamic pricing algorithms reflect the mainstream behavior, which not support such extreme prices (Accenture Strategy, 2019). Altogether, it may be concluded that AI improves the overall performance and the favorable approach is that of analytical. No conclusions will be drawn on tenure, age, or country of origin due to the lack of data on those variables. However, whether this line of reasoning can also be confirmed reversely from the worst-performing players' point of view will be assessed in the next section.

6.3 Determining the Losers

As worst-performing players can be considered those that are beyond the constraints set in the optimization problem in the previous chapter. In other words, those players whose price was beyond 300€ and/or the provided customer value less than 50€. Though, since it is possible in practice that an apartment that is expensive but delivers a high customer value gets rented, only the players whose customer value has been less than 50€ are considered here:

CV BELOW 50€								
EXPERIMENT 1								
TYPE	PRICE	AMENTITIES	CV	PROFIT	GENDER	AGE	COUNTRY	TENURE
4	450	7	40	310	Male	21	Italy	0
3	250	4	30	170	Female	21	Italy	0
3	250	4	30	170	Female	21	Italy	0
EXPERIMENT 2								
TYPE	PRICE	AMENTITIES	CV	PROFIT	GENDER	AGE	COUNTRY	TENURE
2	250	4	30	170	Female	21	Germany	0
1	200	3	10	140	Female	21	Italy	0
2	250	4	30	170	Male	21	Italy	0

Table 15. CV below 50€.

In experiment one, three persons have not reached the customer value of 50€. It is interesting to note that none of these persons played under the type 1 or 2 scenarios, which means that the instructions provided for them were either none or a combination of intuitive and analytical approaches. In the second experiment, there are no worst performing players under type 3, indicating that under the automated pricing no one set their equations so that the customer value would have been below the threshold of 50€. Altogether, these observations support what has been reasoned already before: when the algorithms are let autonomously set the prices, the interests of all the involved parties are taken into account and balanced so that in a long run everyone will be better off. If this logic of reasoning holds, then it means that even if in one case scenario it would be better to choose a high price with lots of amenities with analytical reasoning, *de facto* it is not the most feasible solution if one wishes to keep beating the competition over and over again. Of course, all of this depends on the relative magnitude of supply and demand in the particular case but what has been the competitive context in this game supports the line of reasoning.

Finally, to draw the ultimate conclusions on the worst performing players, their self-assessment and freely written comments will be observed as was done on the winners. Though, not all the players' have provided comments so only those who had are reported below. The results are the following:

SELF-ASSESSMENT; CV BELOW 50€						
['Your profits' equation]	['Value to customer' equation]	[Expert's Advice appeared on screen]	[Yearly averages of price and reviews]	[Reviews and prices of the whole last month]	[Reviews and prices of the last 3 days]	TYPE
EXPERIMENT 1						
Considerably	Considerably	Considerably	Moderately	Considerably	Moderately	4
Slighlty	Slighlty	Slighlty	Moderately	Moderately	Slighlty	3
Slighlty	Considerably	Extremely	Not at all	Slighlty	Extremely	3
EXPERIMENT 2						
Considerably	Extremely	Not at all	Considerably	Moderately	Not at all	2
Moderately	Considerably	Moderately	Moderately	Extremely	Slighlty	1
Considerably	Considerably	Moderately	Extremely	Considerably	Slighlty	2

Table 16. CV below 50€; Self-Assessment.

Comments:

Experiment 1.

CV Below 50€

1. Male, 21, Italy, CV of 40€

*In the first game, I see the tablet and I decide to make the apartament at 300 euros with 5 amenties. So the profit was 200 (=300-5*20) and the value for customer was 50 (= 5*70 - 300). After, in the second game I decide to make the apartament at 450 euros with 7 amenties but i don't rent the apartement.*

2. Female, 21, Italy, CV of 30€

To take my decision I used both intuition and some calculations (like Price - Amenities X 70) to see the result and if it was linked to the starting aim.

Experiment 2.

CV Below 50€

1. Male, 21, Italy, CV of 10€

In the first round I choose to put 5 amenties (more than the average number) and compare with the price of the average satisfaction of our client that was 260€.
I miss the second round.

By analyzing the self-assessments and comments of the worst performing players, it is interesting to observe how in comparison to those that succeeded in the game there seems to be a lower tendency to rely on the provided equations on profits and customer value. The comments, for example, are referring to an approach that is more general and intuitive. Furthermore, it is more apparent from the comments that these players have not succeeded to take into account the whole array of information provided to them and critically assess the significance of each piece of information for the final performance.

This chapter has presented one possible, analytical approach to the winner determination by using the provided information to find an optimal solution that maximizes the profits of the house rental platform entrepreneur. Though, as already noted before, whether this is *de facto* the approach to determine the winners through the computer algorithms is another question. Nonetheless, the reasoning and findings of this chapter support the theory presented in this thesis and the results obtained from the statistical tests. The next chapter shall move on to discuss the entirety of the analyses done in this thesis.

7. Results & Discussion

In short, the results of the conducted statistical tests suggest that AI makes a notable difference in performance by guiding people to be more coherent and 'average' in their performance. Moreover, in that respect, it is found how features such as gender do not seem to make a notable difference when a decision-maker is reasoning with or through AI, which further supports the impact of AI in reasoning processes. Conventionally, it is considered that an analytical approach leads to better and more robust conclusions in price determination contexts. However, some indications are found, which suggest that in face of AI the role of experience and depth of analysis are not so crucial anymore *per se*, implying that strategic intelligence as one of the components of the theoretical model may have less weight when AI is involved. Be as it may, in the following sections the results are discussed in the light of the theory introduced at the beginning of this thesis. Eventually, the hypotheses are addressed and the main research question '*How AI affects decision-making in the P2P house rental context*' is answered.

Humans and Decision-making; the First Experiment

In this thesis, human decision-making has been mainly addressed and analyzed through a theoretical framework where the ultimate human performance is considered consisting of the interplay of analytical skills and strategic intelligence. In short, analytical skills are considered to refer to people's tendency to enjoy thinking and engaging in problem-solving. The concept is also considered to include the wider concept of intuition. However, intuition is conventionally considered as a hindrance to efficient and rational decision-making, particularly in business contexts. This so because it is something that cannot be explained in a coldly rational manner *ex-post*. Strategic intelligence instead, is seen as the ability of a person to take into account the surrounding context and all the relevant data therein. In this respect, the role of experience is thought to play a notable role.

Consequently, the focus has been on the two diverging experiments: The other focusing solely on human reasoning and decision-making (experiment 1), and the another focusing on decision-making powered by AI (experiment 2). It has been observed through the test results that the performance in the first experiment has been more or less coherent, meaning that no notably significant deviations have been spotted – save for that of gender, where a moderate effect has been reported on price and profits. What this could potentially indicate is support for the previously mentioned theory arguing that those people who tend to be more patient (usually women) are also more analytical in their approach and thus deliver better results (Shane, 2005). However, whether this is the case for real is left for subsequent studies to find out. It is considered by the author of this thesis that the sample of this study has not been wide enough for allowing to draw legit conclusions on the data and its support for the study on patience and gender. Though, in this respect, the study on gender and risk-aversion by Nelson (2018) should be taken into account, which refers to a general confirmation bias in academia on the impact of gender in risk-taking and performance (Nelson, 2018). In other words, it is studied by Nelson how *de facto* the gender does not affect the performance when observed in collective. Ultimately, it is considered in the light of the applicable theory and results that gender does not play a significant role in the sense that it would be a predicting factor for the subsequent performance. Even more this line of reasoning is supported when the results measuring the impact of AI are considered: the impact of gender seems to dimmish in the face of AI.

AI and Decision-making; the Second Experiment

Additionally, and in comparison to the first experiment, the second experiment has assessed the impact of AI's involvement in the reasoning processes. Notably, more 'optimal' performances have been reported under the second experiment than in the first one, given that the constrained optimization problem that has been built to solve the pricing problem in chapter six holds. Though, in the second experiment, AI has in some instances automatically set the price, thus leaving less room for analytical approach and human reasoning as a whole. This implies what has been derived from the test results as well: the individual tendencies of being more rational and/or intuitive do not matter that much. What is left to humans is simply the assessment of the soundness of the technologically derived solutions. Overall, it has been observed that a significant difference can be detected from pure human reasoning when AI in automated or augmented form is involved in the process. Therefore, the hypothesis H1b is at least supported. The rest are assessed below.

Answering the Research Question and Addressing the Hypotheses

In the light of the conducted study and research, the hypotheses drafted for the study can be answered in the following manner:

The Hypotheses for the Experiment I

The null hypothesis (H0a) for experiment one was that all the means of the groups are the same when categorized by type. As has become apparent, there are no statistically significant differences between the types of the experiment. Therefore, the answer to the null hypothesis is that there is no single detectable way to approach reasoning and decision-making. All the types are more or less equally likely to lead to success, meaning that the distinguishing factor is something more individual and dependent on each decision-maker and how they perceive the decision-making context. In other words, in the light of the derived results, no pattern or approach can be pointed as the crucial factor for succeeding.

The first alternative hypothesis (H1a) for the first experiment was that the type 3 that encouraged both intuitive and analytical approaches would be the highest performing group. However, since the null hypothesis holds, the alternative one has to be rejected. There are no notable differences among the types. Thus, H0a is supported.

Regarding to the second alternative one (H2a), it has been discovered how there are moderate differences among the gender groups in the first experiment but in the second one these seem to dimmish. Overall, it is considered that there are not enough evidence to support the second alternative hypothesis. Especially, when the contradicting opinions and researches are taken into consideration.

The Hypotheses for the Experiment II

For the second experiment, the null hypothesis (H0b) was that the involvement of AI does not affect performance. Though, this is not the case as has become evident: the Kruskal-Wallis test has demonstrated how it is precisely the variable type that makes the difference (i.e. whether AI is involved and what is the form of it). More precisely, significant differences were found between the types on all the levels but none between gender groups. The effect size on the type was found to be large on price and profits between the different types and moderate on customer value. Thus, as assumed, AI indeed affects decision-making.

The first alternative hypothesis for the second experiment (H1b) was that type 2 and 3 would differ in terms of performance in comparison to the type 1 that has been the group without any AI treatment. This can be confirmed at least partly since there are significant differences between type 3 and the rest on all the dependent variables. Furthermore, this can be observed through the Dunn’s post hoc test after the Kruskal-Wallis test. Therefore, the first alternative hypothesis can be confirmed since even if it is mainly just through the type 3, AI nonetheless improves the performance when compared to the process solely conducted by humans. H0b is rejected while H1b being supported.

The second alternative hypothesis (H2b) was that the AI-augmented reasoning process leads to better performance than that of type 3 or 1. By analyzing the entirety of the test results, and observing the boxplots drawn on them (appendices 2 and 3), it can be noted that this is not the case. Instead, it seems to be reversed. The means of type 3 and type 1 are higher on price and profits in comparison to type 2 but on customer value this is not the case. What this may imply is that AI may assist the decision-makers to obtain better profits but unless they respectively produce customer value that is high enough, they cannot be considered as the ultimate 'winners'. As reasoned before, it is a much more consistent and safer strategy to avoid extreme pricing strategies if one wishes to be consistent over the long run in his/her performance. Therefore, it could be reasoned that even though the means are not higher under the type 2 on price and profits, nonetheless as a whole the type 2 may lead to better performance in the long run since higher customer value is a strong indication for getting an apartment rented over and over again. Though, in the light of the obtained results, the second alternative hypothesis for the second experiment (H2b) is to be rejected.

Managerial Implications

Altogether, this study has focused on studying the array of possible, different reasoning approaches to price determination in the P2P house rental context. Additionally, it has been studied whether AI has a significant, alternating role in the pricing process. By understanding the implications, potential saturation points, and pitfalls for growth, which come along with AI-driven pricing and community management, corporates and their respective managers may better address the need for potential changes in strategy.

Overall, it is considered that the combination of skills and reasoning processes happening behind decision-making are underestimated, and particularly how those tendencies collectively impact firms' performance no matter the business and industry. As noted by Gregory *et al*. (2021), AI offers a possibility for understanding individual customers with such a precision that enables firms and AI to manipulate customers' behavior in a manner that raises a question on the power balance between customers and corporates (Gregory *et al*., 2021). This is something that through careful strategizing can create competitive advantages for firms but also, firms can top the game if they address this fairly and transparently in their strategies; AI-powered firms are not merely predicting customers' behavior anymore but rather engineering it (Morozov, 2019). Altogether, it can be considered that the difference-making factor that should be considered in a corporate's strategy is precisely how to exploit this 'engineering' possibility by parallel providing the transparency and ethical standards for the customers and community (Accenture Strategy, 2019). As demonstrated by the tests performed in this thesis, AI may guarantee you the highest profits but it does not mean that in the long run, you are the winner. After all, you do not sell Ferrari every day.

Consequently, the crucial implication of this study for managers is to understand the array of different approaches that people may use to price their offering on a P2P housing platform. It respectively follows that the managers must understand the implied strategies of AI or better said, how it standardizes the reasoning and price determination processes. This is so since AI has the potential to fundamentally change and alter the way how companies interact with customers, how they compete, and how they can grow within the market (Bughin & Hazan, 2017). Indeed, AI provides the hard data and predictions derived from there but it does not mean that the 'average' performance that it advocates is necessarily the best from the corporate's profit point of view in a long run. It is precisely in this respect where the importance of managers with contextual intelligence and insights is emphasized. Only by grasping the big picture of the hidden and interrelated relationships, it is possible to assess the feasibility of the current corporate strategy and the way forward from there. What this may mean for companies that have not been born as digital is that it is as much a change in doing the business as it is in thinking and approaching it. Thus, before going all-in with AI, corporates should understand the different reasoning process models that their employees may rely on while making those daily business decisions. As discovered in this study, the individual characteristics seem to have more weight and importance for the ultimate performance when pure human decision-making is considered. Therefore, it is equally important to understand how AI affects the human reasoning on the company's side as it is on the side of customers (Fountaine *et al.*, 2019). Ultimately, those companies who will succeed with AI embedded processes are those who are committed to the transformation at every level of the organization, starting from the top management who should embrace the transformation and cross-functional management in order to reshape the processes and practices within the company.

8. Conclusions

This study has focused on human decision-making and AI in the sharing economy context by contributing to the understanding of the process models in decision-making, with and without AI. First, through the theoretical background, a framework has been built to assess human reasoning. Performance has been assessed through the interplay of analytical skills and strategic intelligence. It has overall been concluded that in the process of price determination – in the P2P short-term house rental context – the form of human reasoning does not have a significant role but it seems to be more about the individual characteristics ultimately making the difference when AI is not involved. Though, reversely, gender does not seem to have an impact on the performance when the AI-powered reasoning process is concerned, indicating support for the study on gender and risk-aversion on the confirmation bias, which was referred to in the main text.

In addition, and partly contradicting what has been just said, it has also been observed how the best performing players have all more or less adopted an analytical approach to the reasoning and price determination, regardless of the experiment. This is interesting when it is taken into account that as a collective no such conclusion could have been made on the subjective strength of the analytical reasoning approach. At least in this study. Of course, though, when the 'winners' have been analyzed only a couple of them have been assessed. Thus, not that much weight should be given to those conclusions. Be as it may, a certain level of risk-aversion can be interpreted from the analyzed comments and responses: there is no point in excessive risk-taking for better profits

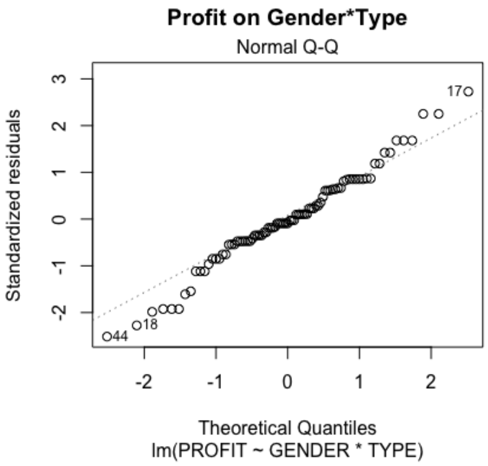
Nonetheless, the main focus and interest in this thesis have been on the impact of AI on performance in the P2P house rental context. Indeed, a clear difference has been seen between the groups that used AI in the reasoning processes in comparison to those who did not. Overall, the clearest 'winner' in terms of performance seems to have been fully automated AI reasoning. In other words, minimal human involvement in contexts such as price determination seems to lead to beating the market most frequently. In the light of the theory introduced in this thesis, this makes sense since humans tend to be bounded in their rationality, relying heavily on the so-called rules of thumb, or heuristics. However, as said, full reliance on automation does not necessarily guarantee the best profits for service enablers and providers, nor the highest customer value for the customers. What automation delivers instead, is an overall balance among the parties' interests, guaranteeing that they stay engaged and on the platform, keeping (re)creating the network effects. Interestingly, this raises the question of whether supply and demand have the primary role in price determination processes anymore. Or better say, is the supply and demand organic anymore if it is powered, engineered, and constantly modified by AI?

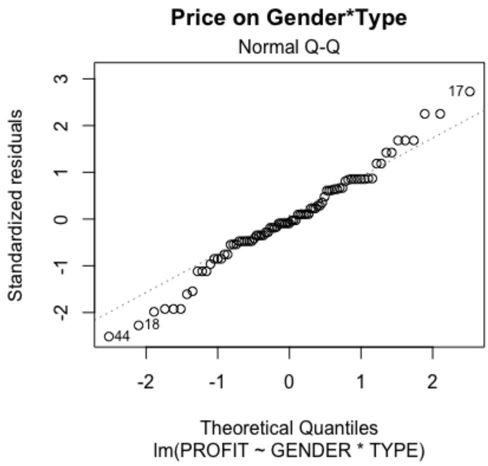
Overall, the results have been obtained by conducting the so-called Kruskal-Wallis test and the applicable post hoc tests. However, the obtained results and insights do not come without limitations. The results' overall applicability can be questioned due to the respectively small sample size and its homogeneity in terms of age, nationality, and tenure of the respondents. Neither it is said that the definitions and the constructed theoretical model are the most accurate ones for clustering the data at hand and to draw the subsequent conclusions on it. Though, as always, delimitations have to be made, which hopefully inspire future studies on the subject.

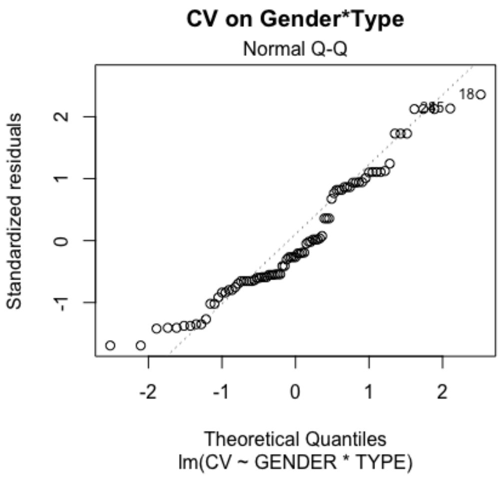
Additionally, from a corporate strategy point of view, AI offers an attractive avenue for engineering the customers' reasoning and decision-making processes towards more standardized ones. Though, what should be kept in mind, however, is what was already said before: it is as much a change in doing the business as it is in thinking and approaching it. Thus, to fully top the competition in AI-driven platform businesses, a shift in the mindsets behind the management is needed if the company has not been born as digital.

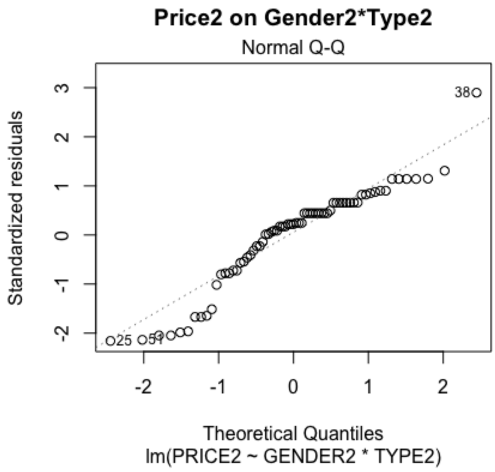
To sum up: several observations stemmed from the research conducted in this thesis: AI affects the decision-making process in P2P house rental contexts, primarily by manipulating the supply and demand. More precisely, AI alters the price determination process by setting (implicit) limits for the prices, thus guiding the service providers towards a more homogenous array of prices. The conventional pricing strategies seem to diminish in their authority. However, it has been observed that even though automated price determination provides fast and efficient suggestions while guaranteeing good profits, it does not emphasize customer value as much as those forms of reasoning where humans are involved. This is no surprise but something for platform managers to keep in mind when determining the strategies that aim at keeping the network and platform community together and engaged. Ultimately, the role and impact of AI in decision-making are to assist and support humans in their analysis, and either confirm or reject their 'gut feelings' on the premises. Interestingly, for subsequent strategies an analogy from game theory and dominance solvable games by iteration can be sensed.

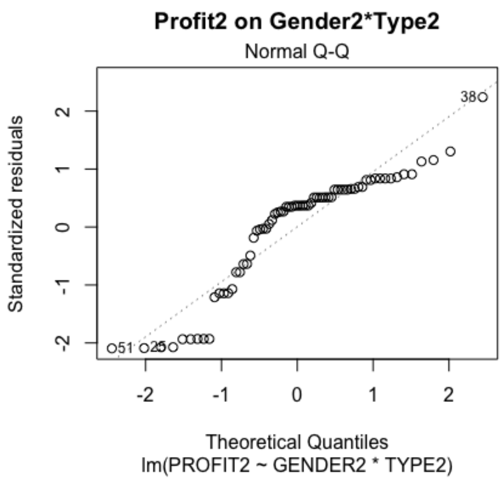
Appendix 1. Assessing the Normality of the Data

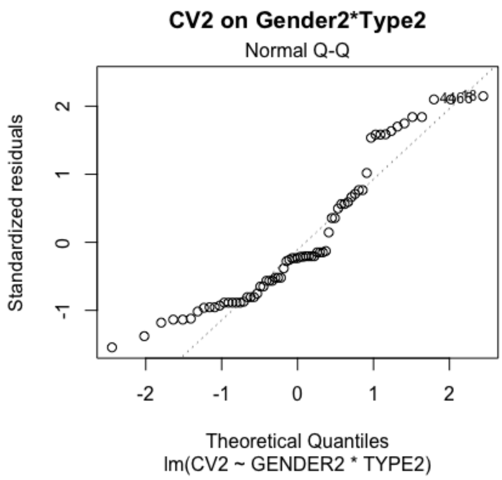




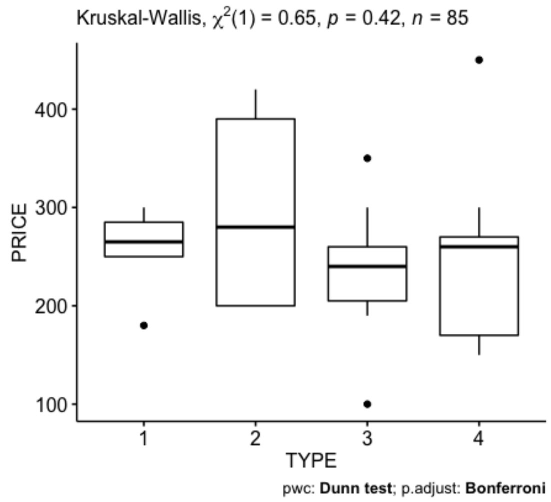


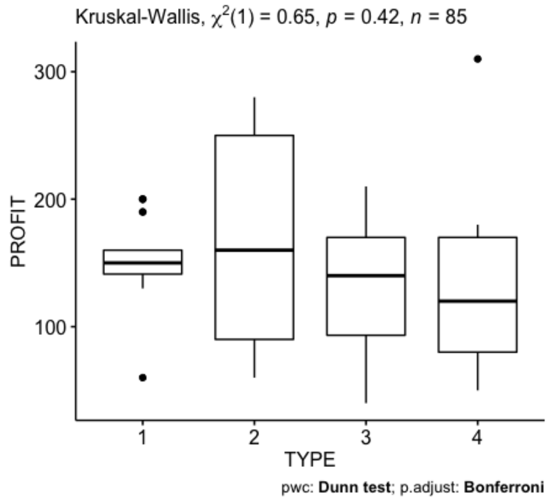


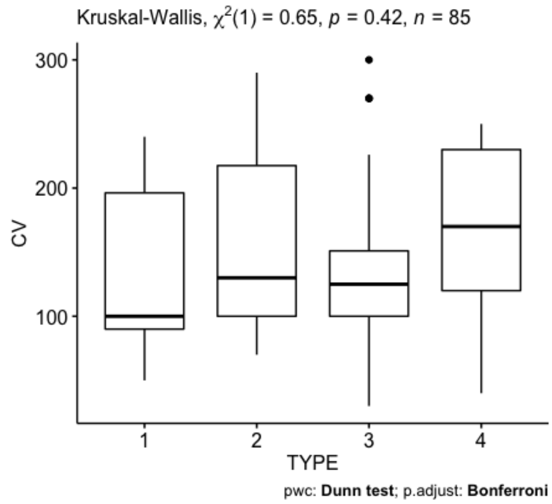


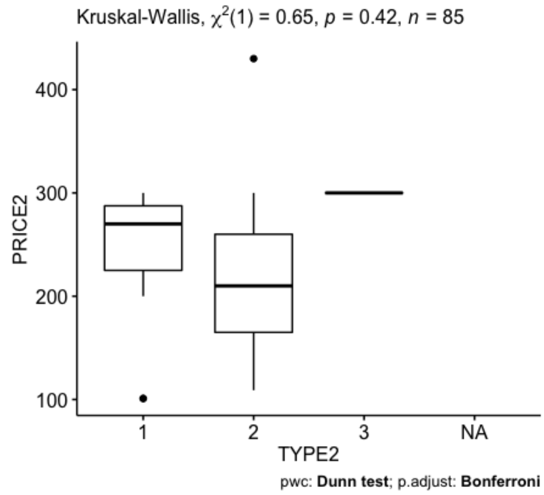


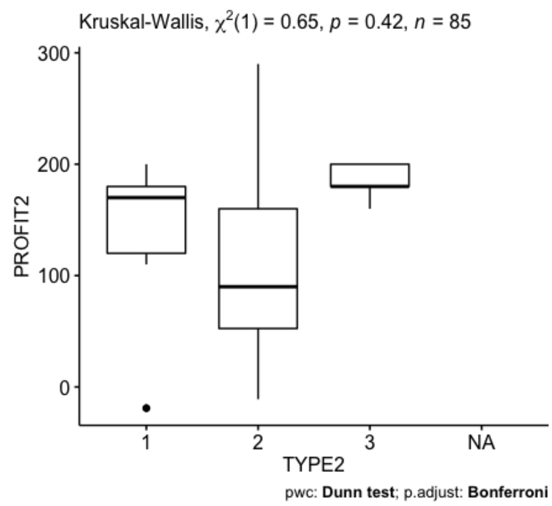
Appendix 2. Kruskal-Wallis Test by Type

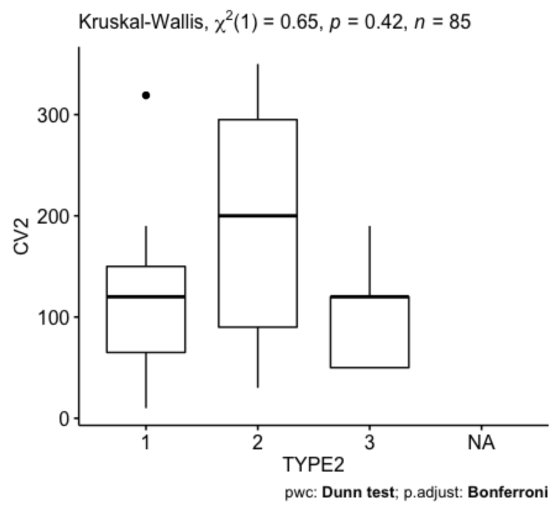




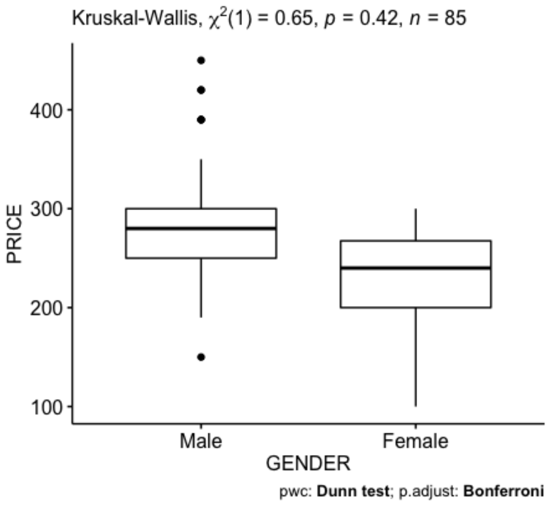


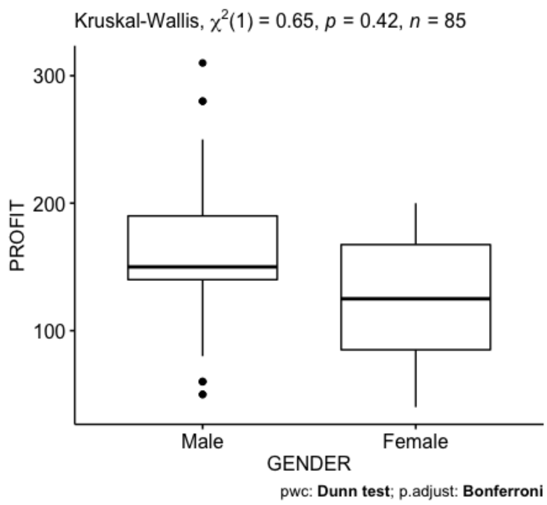


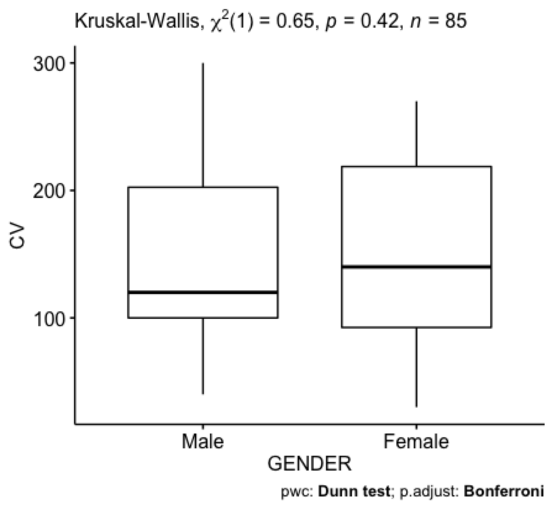


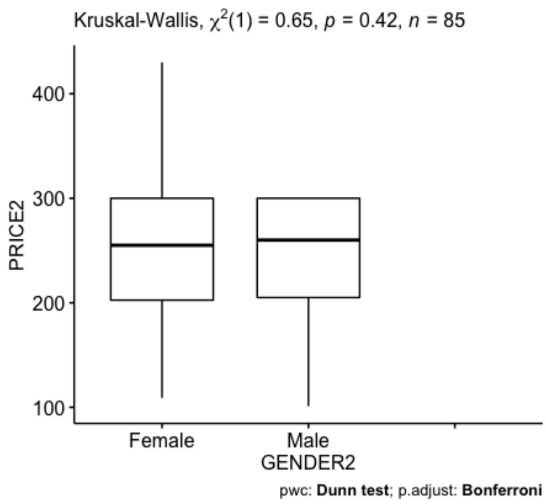


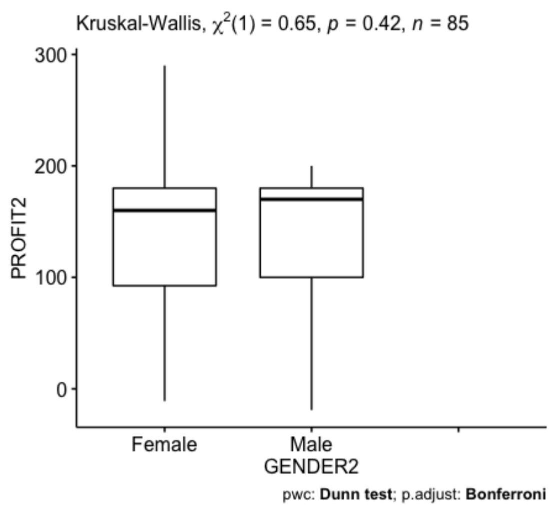
Appendix 3. Kruskal-Wallis Test by Gender

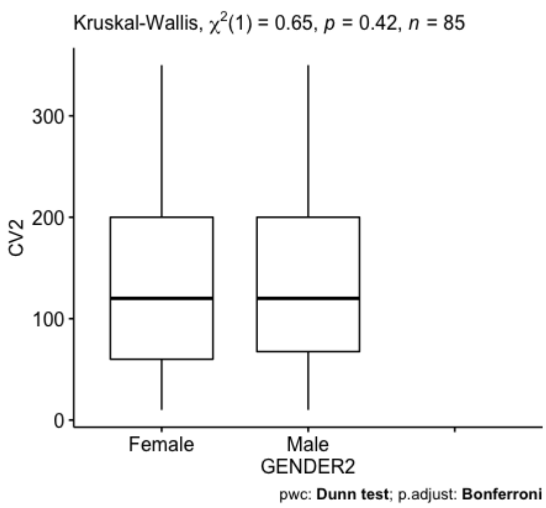












Appendix 4. The Survey's Statements

The Survey

In this appendix, the statements of the survey are clustered according to the *analytical skills – strategic intelligence* division as modeled in the theoretical model before. Though, it should be kept in mind that the classification is not absolute but rather illustrative to provide the reader a better understanding of the entire experiment and how it aims at measuring and assessing the reasoning tendencies. For example, it should be noted in respect to the statements falling under the concept of analytical skills that in the statistical analyses, analytical skills are defined and measured as one independent variable and not according to the following more detailed clustering.

Statements Measuring Analytical Skills

The Statements Measuring *Need for Cognition*:

'*[..] need for cognition is a concept [..] measuring self-reported interest towards tasks that are more or less abstract and (may) need logical thinking and reasoning to be solved. [..] an individual tends to engage and enjoy pure thinking. It is a desire and need to structure situations and things in meaningful, integrated ways* (Cacioppo & Petty, 1982, p.116-117; Lins de Holanda Coelho *et al*., 2020, p.1870). In the light of this definition, the following statements from the survey have been identified as reflecting more or less this dimension of the analytical skills concept:

- I try to avoid situations that require thinking in depth about something
- I enjoy intellectual challenges
- I do NOT like to have to do a lot of thinking
- Thinking is NOT my idea of an enjoyable activity
- I enjoy solving problems that require hard thinking
- I am NOT a very analytical thinker
- I prefer complex to simple problems
- Thinking hard and for a long time about something gives me little satisfaction
- I do NOT reason well under pressure
- Learning new ways to think would be very appealing to me

The Statements Measuring *Cognitive Reflection*:

In general, cognitive reflection is defined as: '*A direct measure of a person's ability to reason. Furthermore, two types of cognitive processes can be distinguished: one which requires a minimal amount of conscious deliberation and another that is a process requiring slower, more reflective behavior. Moreover, a correlation between patience and cognitive abilities is found and in discussion on cognitive reflection it is often referred to the wider concept of intuition, which is often conceptualized as a method of deciding that is based on fast, non-conscious recognition of patterns and further association of those patterns, leading ultimately to judgment* making (Shane, 2005, p.25-29)'.

- I'm not that good at figuring out complicated problems
- I like to rely on my intuitive impressions
- I enjoy thinking in abstract terms
- I have no problem in thinking things through carefully
- Knowing the answer without having to understand the reasoning behind it is good enough for me
- I do NOT have a very good sense of intuition
- Using my "gut- feelings" usually works well for me in figuring out problems in my life
- I believe in trusting my hunches
- Intuition can be a very useful way to solve problems
- I often go by my instincts when deciding on a course of action
- I trust my initial feelings about people
- When it comes to trusting people, I can usually rely on my gut feelings
- If I were to rely on my gut feelings, I would often make mistakes
- I do NOT like situations in which I have to rely on intuition
- I think there are times when one should rely on one's intuition
- I hardly ever go wrong when I listen to my deepest "gut- feelings" to find an answer
- My snap judgments are probably NOT as good as most people's
- I tend to use my heart as a guide for my actions
- I can usually feel when a person is right or wrong, even if I can't explain how I know

- I suspect my hunches are inaccurate as often as they are accurate

Statements Measuring Strategic Intelligence

Strategic intelligence, respectively, is defined as '*the collection, analysis and dissemination of information with high strategic relevance. This is to say that in practice and competitive situations people are required to be able to anticipate what the competitors will and would rationally do* (Kuosa, 2011, p.458).'

- I am NOT very good in solving problems that require careful logical analysis
- Reasoning things out carefully is NOT one of my strong points
- I am much better at figuring things out logically than most people
- I have a logical mind
- Using logic usually works well for me in figuring out problems in my life
- I usually have clear, explainable reasons for my decisions
- I think it is foolish to make important decisions based on feelings
- I do NOT think it is a good idea to rely on one's intuition for important decisions
- I generally do NOT depend on my feelings to help me make decisions
- I would NOT want to depend on anyone who described himself or herself as intuitive

Appendix 5. RStudio Code

“””

Created: Sat Apr 2 2021
Last Modified: Sun May 30 2021

The following lines of codes contain the algorithms inputted to the RStudio software for the computations of the statistical tests and the applicable graphs.

More precisely, the process for deriving the descriptive statistics from the dataset is breakdown together with the normality check of the data (see appendix 1), outlier visualization, the Kruskal Wallis test (appendix 2 and 3), and the modeling of the constrained optimization problem.

The following lines of code are simplified and any confusing repetition has been cut when considered proper. Comments and clarifications follow when the symbol ‘#’ appears.

Author: Maria Espo

“””

```
sink(file = "WORKBOOK.txt") #Transfer the output of R Studio to Excel

#Import dataset from Excel file
RESULTS <- read.csv("~/Documents/MASTER THESIS/CS/STUDY 1/EXCELS/
WORKBOOK.csv", sep=";")

#install the required packages for the subsequent computations
library(ggplot2)
library(mvoutlier)
library(ggpubr)
library(ggrepel)
library(ggsci)
library(ggsignif)
library(munsell)
library(nloptr)
library(Rcpp)
library(readr)
library(rio)
library(scales)
library(stringr)
library(tibble)
library(tidyselect)
library(tidyverse)
library(broom)
library(backports)
library(colorspace)
```

```
library(curl)
library(data.table)
library(dbplyr)
library(farver)
library(gtable)
library(highr)
library(haven)
library(lpSolve)
library(magrittr)
library(psych)
library(quantreg)
library(rlang)
library(rstatix)

###############SUMMARY STATISTICS#################
#Descriptive Statistics grouped by GENDER
describeBy(WORKBOOK_NUMERICAL,WORKBOOK_NUMERICAL$`WORKBOOK
$GENDER2`)
#Descriptive Statistics grouped by AGE
describeBy(WORKBOOK_NUMERICAL,WORKBOOK_NUMERICAL$`WORKBOOK
$AGE2`)
#Descriptive Statistics grouped by TYPE
describeBy(WORKBOOK_NUMERICAL,WORKBOOK_NUMERICAL$`WORKBOOK
$TYPE2`)

#Single Box-plot GENDER
GGO_PRO_G<-ggboxplot(x="GENDER", y= "PROFIT", data = WORKBOOK)
GGO_CV_G<-ggboxplot(x="GENDER", y= "CV", data = WORKBOOK)
GGO_PRI_G<-ggboxplot(x="GENDER", y= "PRICE", data = WORKBOOK)

#Single Box-plot AGE
GGO_PRO_A<-ggboxplot(x="AGE", y= "PROFIT", data = WORKBOOK)
GGO_CV_A<-ggboxplot(x="AGE", y= "CV", data = WORKBOOK)
GGO_PRI_A<-ggboxplot(x="AGE", y= "PRICE", data = WORKBOOK)

#Single Box-plot TYPE
GGO_PRO_T<-ggboxplot(x="TYPE", y= "PROFIT", data = WORKBOOK)
GGO_CV_T<-ggboxplot(x="TYPE", y= "CV", data = WORKBOOK)
GGO_PRI_T<-ggboxplot(x="TYPE", y= "PRICE", data = WORKBOOK)

# Box-plot arranged in a single sheet
figure <- ggarrange(GGO_PRO_G, GGO_PRO_G, GGO_PRI_G,GGO_PRO_A,
GGO_PRO_A, GGO_PRI_A,GGO_PRO_T, GGO_PRO_T, GGO_PRI_T, labels =
c("A", "B", "C", "D", "E", "F", "G", "H", "I"), ncol = 3, nrow = 3)
figure

################ASSUMPTIONS#################
#N.B. At this point the datafile has been renamed from 'WORKBOOK' into
'RESULTS'
```

```
#RESULTS_NUMERICAL_short<-RESULTS_NUMERICAL
#outliers <- qq.plot(RESULTS_NUMERICAL[c("RESULTS$TYPE",
"RESULTS$GENDER","RESULTS$AGE", "RESULTS$PRICE",
"RESULTS$PROFIT", "RESULTS$CV")])
#outliers # show list of outliers

#TEST for Normality Exp 1
qqnorm(RESULTS_NUMERICAL$`RESULTS$PRICE`, main = "Price Normality
Check")
qqline(RESULTS_NUMERICAL$`RESULTS$PRICE`)
shapiro.test(RESULTS_NUMERICAL$`RESULTS$PRICE`)
qqnorm(RESULTS_NUMERICAL$`RESULTS$PROFIT`, main = "Profit Normality
Check")
qqline(RESULTS_NUMERICAL$`RESULTS$PROFIT`)
shapiro.test(RESULTS_NUMERICAL$`RESULTS$PROFIT`)
qqnorm(RESULTS_NUMERICAL$`RESULTS$CV`, main = "Customer Value
Normality Check")
qqline(RESULTS_NUMERICAL$`RESULTS$CV`)
shapiro.test(RESULTS_NUMERICAL$`RESULTS$CV`)
#N.B. the same code applies for the experiment 2 but ‘2’ is just added at the end of
each variable

#OUTLIERS THROUGH BOXPLOTS
ggplot(RESULTS) +
 +    aes(x = "TYPE", y = PRICE) +
 +    geom_boxplot(fill = "#0c4c8a") +
 +    theme_minimal()
boxplot.stats(RESULTS$PRICE)$out
#ETC.

################KRUSKAL-WALLIS TEST#################
#N.B. here the file is called ‘WORKBOOK’ again

#KRUSKAL TEST - Nonparametrical Analysis GENDER
kruskal.test(WORKBOOK$PRICE ~ WORKBOOK$GENDER, data = WORKBOOK)
kruskal.test(WORKBOOK$PROFIT~ WORKBOOK$GENDER, data = WORKBOOK)
kruskal.test(WORKBOOK$CV ~ WORKBOOK$GENDER, data = WORKBOOK)

#KRUSKAL TEST - Nonparametrical Analysis AGE
kruskal.test(WORKBOOK$PRICE ~ WORKBOOK$AGE, data = WORKBOOK)
kruskal.test(WORKBOOK$PROFIT~ WORKBOOK$AGE, data = WORKBOOK)
kruskal.test(WORKBOOK$CV ~ WORKBOOK$AGE, data = WORKBOOK)

#KRUSKAL TEST - Nonparametrical Analysis TYPE
kruskal.test(WORKBOOK$PRICE ~ WORKBOOK$TYPE, data = WORKBOOK)
kruskal.test(WORKBOOK$PROFIT ~ WORKBOOK$TYPE, data = WORKBOOK)
kruskal.test(WORKBOOK$CV~ WORKBOOK$TYPE, data = WORKBOOK)

#Effect Size by Type
WORKBOOK %>% kruskal_effsize(PRICE ~ TYPE)
```

```
WORKBOOK %>% kruskal_effsize(PROFIT ~ TYPE)
WORKBOOK %>% kruskal_effsize(CV ~ TYPE)

#Effect Size by Gender
WORKBOOK %>% kruskal_effsize(PRICE ~ GENDER)
WORKBOOK %>% kruskal_effsize(PROFIT ~ GENDER)
WORKBOOK %>% kruskal_effsize(CV ~ GENDER)
#the same code for experiment 2 but with '2' at the end of each variable

#Multiple Pairwise Comparison by Dunn's Test
pwc <- WORKBOOK %>%
  dunn_test(PRICE ~ TYPE, p.adjust.method = "bonferroni")
pwc
#ETC.for the other variables by type and by gender and the same procedure for exp.
2

#Visualisaion and Reporting
# Visualization: box plots with p-values
pwc <- pwc %>% add_xy_position(x = "TYPE")
ggboxplot(WORKBOOK, x = "TYPE", y = "PRICE") +
  stat_pvalue_manual(pwc, hide.ns = TRUE) +
  labs(
    subtitle = get_test_label(res.kruskal, detailed = TRUE),
    caption = get_pwc_label(pwc)
    )
#ETC.for the other variables by type and by gender and the same procedure for exp.
2


#########THE CONSTRAINED OPTIMIZATION PROBLEM###########
> # Objective Function
>
> f.obj <- c(1, -20)
> f.con <- matrix(c(-1, 70, 1,0, 0, 1), nrow = 3, byrow = TRUE)
> f.dir <- c(">=", "<=", "<=")
> f.rhs <- c(50, 490, 7)   # 50 is the minimum observed CV such that house is rented,
while 490 is the maximum price such that CV>0, 7 is the maximum amenities
rentable
> res <- lp("max", f.obj, f.con, f.dir, f.rhs, int.vec = 1:3)
> print(res)
Success: the objective function is 300
> res$solution
[1] 440   7
```

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Thesis Summary

The research conducted in this thesis has aimed at analyzing whether there is a difference between the different decision-making process models in terms of performance in short-term house rental platforms. This has been investigated from two different points of view: instances where only human decision-making is concerned, and instances where the human decision-making has been either augmented by AI or replaced (automated) by it. It has also been analyzed whether certain characteristics of a decision-maker have played a role in the approach and results that one has obtained.

Below, a summary of the main arguments of the thesis is presented chapter by chapter.

Chapter 2; Introduction

The study conducted in this thesis contributes both to the research gap on the interplay of intuition and analysis in human decision-making as well as to the one on the role of AI in that process. Overall, it has been found how there is no clear understanding of the different process models to which humans tend to rely on while determining prices and making choices in that respect. Furthermore, it is unclear how certain characteristics such as the gender of the decision-maker may affect one's ability to make profits and compete in such a setting. In the study, these questions are analyzed through an experimental survey that has observed the difference between differing decision-making settings and process models. The focus is on the division between instances where only humans are involved in the reasoning process and on those where AI is involved. To further strengthen the analysis done in the study, a theoretical model has been built to assess and evaluate the performance of the survey's respondents. Altogether, it is considered that by addressing these questions and gaps it is possible to derive insights for both managers supervising short-term housing platforms and platform entrepreneurs making business therein. Overall, the arguments of the study seek to assess whether the involvement of artificial intelligence renders void the traditional competitive strategy based on the assumption that customers independently determine their willingness to pay for a product or service and that the hosts would be free to value their offerings as they wish.

Chapter 3; Theoretical Background

The arguments made, and the subsequent hypotheses drafted in this thesis have been done in the light of the applicable theory. The first important notation stemming from the theory is the fact that human minds are considered of being inflicted with cognitive biases, which negatively affect their ability to exercise judgment in predictable ways (Einhorn, 2021). It is from these imperfections of human minds where the need for AI comes from. Logically, parallel to the benefits of AI comes a new way to approach reasoning, decision-making, and business altogether. Consequently, what this means for platforms like Airbnb and the process of price determination therein, is that new performance metrics are needed and the price determination must take more variables into account, the prices being much more dynamic and volatile (Van Alstyne *et al*., 2020; Sedkaoui & Khelfaoui, 2020). Altogether, it is noted how the conventional way of thinking about pricing as a result of public perception of value does not hold anymore. Rather, the companies are manipulating and engineering the supply and demand (Morozov, 2019). It is theorized that in the context of P2P house renting, the price determination does not follow *prima facie* any specific pricing theory but the final price is a result of the non-linear influence of listing variables on room pricing if of course the price has not been automatically set by the service enabler. Thus, the key in this respect for platform entrepreneurs lays in the identification of the variables that appear to be the key determinants of tourist accommodation prices (Chattopadhya & Mitra, 2020, p.603). Ultimately, it is considered to be a challenge for platform managers on the corporate level to manage the network and its offerings in a way that balances the interests of all the parties involved (Church, 2017; Kumar *et al*., 2018).

Secondly, in addition to the theoretical implications, in this chapter, the theoretical model has been built and introduced, which is ultimately used in the data analysis to cluster the collected data. The model is based on assumption that human cognition is considered varying and being a dependent variable of the competitiveness of markets, implying that individuals differ in terms of the analytical effort they put into reasoning and decision-making in general. Therefore, a distinction has been made between analytical and intuitive approaches. It is considered that the difference between intuitive reasoning to rational, purely analytical one lays in the speed of processing information and the linearity and logicality of reasoning. Rational decision-making can always be reconstructed and explained afterward whereas in the case of intuition it is often unclear how the decision-maker came to that one particular conclusion (Calabretta *et al*., 2017). It is implied that a rational decision-maker cannot easily accommodate intuitive thinking and vice versa. Ultimately, in the light of the data, it will be concluded whether intuition or analysis seems to have a bigger role in the decision-making processes and what role does AI seems to play in that process respectively. Additionally, in this respect researches on the impact of gender are referred to, giving rise to arguments on the impact of individual characteristic on performance. Altogether, the theoretical model drafted in this chapter is built to be an interplay of analytical skills and strategic intelligence, and this interaction is assessed on the ultimate performance of the respondents. Finally, references and considerations from game theory are briefly touched upon.

Consequently, at the end of the chapter, the hypotheses are drafted and the reasoning behind them is elaborated. The hypotheses are the following:[2]

H0a: There is no single way to conduct a human reasoning process to succeed. Intuitive or analytical approaches are both as likely to lead to the highest performance.

H1a: *Combining intuitive and analytical reasoning leads to the highest performance.*

H2a: *There is a clear difference between the different gender groups in terms of performance.*

H0b*: Involvement of AI does not significantly affect performance. No notable variation between the three types can be detected.*

H1b: Use of AI in decision-making improves performance. To rely on AI in reasoning is better than a reasoning process merely conducted by a human.

H2b: The use of AI to augment a reasoning process improves the performance, meaning augmentation outperforms automation in a reasoning process.

Chapter 4; Experimental Design

There is a close relationship between the design of an experiment and the statistical analysis conducted on the collected data. A successful experimental study should be able to manipulate the constant variables in a way that allows concluding whether a change of variables is a cause of the manipulation (Ross & Morrison, 2003). This is precisely what this thesis aims at doing: studying the (non)existing interactions among the independent variables of gender and type,

[2] The notation 'a' refers to the first experiment whereas 'b' refers to the second one.

and eventually conclude whether price, profits, or customer value are dependent on the manipulations made on the independent variables. The hypotheses drawn for the analysis of this study are supported by the theoretical resources presented in chapter three.

The data for the analysis has been collected through a survey/game that assesses decision-making process models. The primary focus has been on the game part, which assesses the performance of the players and the 'avenues' they have taken to their pricing decisions. The task in the game is to act as a host of a holiday house and determine the price and the number of amenities for it. The experiment is a randomized one and a different scenario is randomly allocated to each player. The players are provided with information on the historic bookings, reviews, and prices. Additionally, the formulas for profits and customer value are given, which are the following: profits=price-(number of amenities x 20€), customer value=(amenities x70€)-price. The apartment that in the end produces the highest value for customers is booked. The winner is ultimately the person who manages to obtain the highest profits, given s/he manages to rent his/her apartment. The randomly allocated scenarios that a player may encounter are the following:

- Experiment I; Studying Human Decision-making:
    1. Intuitive approach encouraged;
    2. Analytical approach encouraged;
    3. Combination of both supported;
    4. No specific guidelines are given.
- Experiment II; Decision-making with AI
    4. Reasoning without any help from AI;
    5. Automated price determination;
    6. Augmented price determination process.

Finally, the players are asked to indicate on a scale from 'not at all' to 'extremely' how much the different pieces of information given to them affected their decision-making process. It is this information that enables the later, holistic analysis of the best-performing players. In the end, the players are additionally asked to indicate their gender, age, country of origin, and years of working experience.

The precise analyses in the thesis are computed by exploiting the RStudio software. As statistical tests, the Kruskal-Wallis test and the Dunn's post hoc test have been chosen since they are considered to be particularly suitable for the data after discovering that the data is not suitable for parametrical tests such as ANOVA since it is not normally distributed, and the assumption on the homogeneity of variance has not been met. As independent variables, the precise scenario [type] that a player has faced and gender have been considered. Respectively, price, profits, and customer value are treated as dependent ones since these ultimately enable the analysis of performance. The alpha level i.e. the significance level in the performed statistical tests of this thesis is chosen to be the standard .05. Altogether, following the precise steps for the statistical tests and conducting the computations on RStudio have guaranteed the validity and reliability of the conclusions. No theoretical claim or argument has been made without support from another source.

Chapter 5; Kruskal-Wallis Test

The test has been chosen based on the drafted hypotheses, and the characteristics that the dataset has shown. This is to say, first, that since the data was found out to be not normally distributed (appendix 1), a non-parametrical test such as the Kruskal one had to be chosen. Secondly, the nature of the drafted hypotheses indicated a test that would enable comparison between more than two groups on the independent variables in respect to the dependent ones. Additionally, the chosen test is optimal for randomized experiments such as the one studied in this thesis. By performing the Kruskal test, it is possible to observe whether there seem to be significant differences among the dependent variables when grouped by either gender or the type of experiment. The test has been run with the RStudio, allowing to measure the effect size through the squared eta that measures and observes the variance in percentiles in the dependent variables as explained by the independent ones. It has been discovered how gender does not seem to have a real impact in the second experiment but it seems to play a moderate role in the case of the first one. Altogether, these results seem to support at least partly the hypotheses made in this thesis; gender seems to have a slight impact when pure human decision-making is concerned but this effect diminishes once the AI is relied on in the reasoning process. More precisely, in the experiment one significant difference has been reported in price between types (p=0,0448), and also significant differences were found in price (p=0,000185) and profits (p=0,00000256) when grouped by gender in experiment one. In the second experiment, significant differences were found in all the dependent variables when grouped by type (price p= 0,000000492; profit= 0,00000256; CV=0,0125) but none when grouped by gender.

Additionally, the effect size of the results has been examined where the results demonstrated a large effect in price (efs=0,330) and profits (efs=0,290) when grouped by type in experiment two. Moderate effects, among others, were reported in price (efs=0,0624) and profits (efs=0,0299) in experiment one when grouped by gender.

Finally, on the significant results, a more detailed pairwise comparison has been conducted. From these results, it can be observed how the significant differences were between males and females on price (p=0,00185) and profits (p=0,00721) in experiment one. In the experiment two, statistically significant differences were found in price between the groups 1 and 3 (p=0,0018) and 2 and 3 (p= 0,000000212) but also in profits (p=0,0142 for 1&3; p= 0,00000134 for 2&3). The applicable boxplots visualizing these findings can be found in appendices 3 and 4.

Chapter 6; A Constrained Optimization Problem

In addition to the main analyses conducted in this study, an extra qualitative analysis has been conducted to provide one possible and more detailed analytical approach to the pricing problem. This has been done by constructing a constrained optimization problem by relying on the Simplex algorithm. The objective function for the problem has been built based on the information provided in the game on the historical prices, bookings, and reviews. As constraints, the equations on profits and customer value have been used together with the number of amenities. Altogether, the analysis conducted in this chapter has demonstrated how the best performing players seem to fall under the types that emphasized the analytical approach to price determination. Additionally, in the first experiment, the strongest impact seems to have been on the provided equations to calculate the profits and customer value, when the comments of the players are considered. The last month’s booking information has also played a strong but varying role in the reasoning process. Captivatingly, the expert advice has not played almost any role at all among the best-performing participants of the first experiment. Furthermore, by observing the comments of some of the best performing players it can be observed how it has been a strongly analytical approach that these players have taken to the price determination dilemma. Be as it may, what seems to be common for the majority of the responses is a certain level of risk aversion and a tendency to rely on average performance instead of excessive risk-taking.

Chapter 7; Results and Discussion

The results of the conducted statistical tests suggest that AI makes a notable difference in performance by guiding people to be more coherent and ‘average’ in their performance. Instead, gender does not seem to make such a difference when a decision-maker is reasoning with or through AI. Overall, it is found that conventionally a more analytical approach leads to better and more robust conclusions in price determination contexts. However, some indications are found, which suggest that in face of AI the role of experience and degree of analysis are not so crucial anymore per se, implying that strategic intelligence as one of the components of the theoretical model may have less weight when AI is involved.

More precisely, the performance in the first experiment has been more or less coherent, meaning that no notable statistically significant deviations have been spotted – save for that of gender, where a moderate effect has been reported on price and profits. There are no notable differences among the types. In the second experiment, the effect size on the type was found to be large on price and profits between the different types and moderate on customer value. Thus, as assumed, AI indeed affects decision-making. In more technical terms, the hypotheses H0a and H1b are supported whereas H1a, H0b, H2a and H2b have been rejected: there is no single way to reason and make decisions in order to succeed but technology notably improves the chances of obtaining better profits and overall performance in P2P house rental context.

Overall, the results are considered to imply that AI may assist the decision-makers to obtain better profits but unless they respectively produce customer value that is high enough, they cannot be considered as the ultimate 'winners' since high customer value is found to be a strong indication for getting an apartment rented over and over again. Be as it may, AI offers a possibility for understanding individual customers with such a precision that enables the firms and AI manipulates customers' behavior in a manner that raises a question on the power balance between customers and corporates (Gregory *et al.* 2021).

Chapter 8; Conclusions

Several observations stemmed from the research conducted in this thesis: AI affects the decision-making process in P2P house rental contexts, primarily by manipulating supply and demand. More precisely, AI alters the price determination process by setting (implicit) limits for the prices, thus guiding the service providers towards a more homogenous array of prices. The individual attributes and tendencies of decision-makers seem to diminish in their importance when faced with AI. Respectively, the conventional pricing strategies appear to weaken in their authority. However, it has been observed that even though automated price determination provides fast and efficient suggestions while guaranteeing good profits, it does not emphasize customer value as much as those forms of reasoning where humans are involved. This is no surprise but something for platform managers to keep in mind when determining the strategies that aim at keeping the network and platform community together and engaged.

Ultimately, the role and impact of AI in decision-making are to assist and support humans in their analysis, and either confirm or reject their ‘gut feelings’ on the premises. Interestingly, for subsequent strategies an analogy from game theory and dominance solvable games by iteration can be sensed, the fundamental question and critical success factor is the type of AI involvement in these processes.