Management Project

Positioning Effect on Online Travelers' Booking Behavior in Horizontal vs. Vertical Layout

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Abstract

This study examines the decision-making process in consumer behavior with a focus on tourism. It reveals that every decision-making model in a complex environment includes an irrational influencing factor that contributes to the final decision on choosing a travel product: destination to go to, hotel to stay in, transportation to take, activity to do etc. In addition, people taking decisions in such complex environments dominated by multiple options and constraints are even more susceptible on applying mental shortcuts, such as heuristics, as there is human cognitive limitation on arriving to an optimal choice by weighting in all the given factors. Hence, people will simplify the problem by applying mental shortcuts to arrive not necessarily to an optimal decision but to a satisficing one. This study focusses on one of the heuristics, called positioning effect, that is consistently applied in choosing a travel product, a hotel, from a given list. This is especially relevant in nowadays era where most of the people choose and book travel products online. In particular consumers choose hotels from a given list presented horizontally or vertically.

This research shows, through experimental testing, that when presenting hotels in a horizontal list, their position matters in the selection criteria. The experiment was conducted using 1000 participants from Amazon Mechanical Turk online panel. The participants had to choose one hotel from a list of 10. They were randomly assigned to 10 different experiment conditions, where each of the 10 hotels changed its position. Results demonstrate a nonlinear effect of hotel position in the list on choice: hotels positioned at the beginning of the list are more likely to be chosen.

In addition, using a non-negative matrix factorization technique to analyze the experiment results, one can separate the irrational choices such as heuristics (positioning effect) from rational ones (based on attributes assessment). The introduction of this technique is useful for the literature when analyzing decision-making that can be both rational and irrational, being able to discover the latent features underlying the interactions between two different kinds of entities (such as rational vs. irrational factors that lead to a final choice).

Furthermore, Online Travel Agencies could use this technique in order to determine what part of the product influence people decision: evaluation criterion based on heuristics vs. choice criterion based on attributes. Knowing what exactly impacts the users is very valuable when doing multiple changes in the same time, such as developing new user interfaces, plus adding or removing attributes, plus using different heuristics based on framing effect, positioning effect, loss aversion etc. Usually when OTAs are doing multiple changes at once, it's hard to tell what change impacted negatively or positively the users. This technique will help separate different factors and help analyze what influence customer decision the most.

This is also the first study that analyzes the positioning effect in a horizontal presentation with a high-involvement decision-making, such as choosing an expensive hotel to stay at for a week. Its implications for Online Travel Agencies are numerous, especially on leveraging positions in a list to promote specific travel products. In addition, OTAs can drive discovery of specific products on their own site or on other marketing channels by leveraging top positions in a horizontal list.

Introduction

The battle for bookings among online travel brands is in full force. In an age where travelers have literally hundreds of choices to book a simple hotel, the competition has never been more intense amongst the Online Travel Agencies. (Travelport, 2019) 70% of leisure travelers have used online travel agency when looking for travel inspiration in the last year. (Travelport, 2019). In US, OTAs have almost 30% of travelers using their sites (see Fig A).

Fig A. Website used for destination selection, last trip, share % (Phocuswright, 2019)

In addition, OTAs in particular spend significant portions of their marketing budget trying to turn lookers into bookers.

In order for OTAs to win this battle, they have to understand the travelers booking journey and their decision-making process. This is not a simple task as travelers' journey and their decision-making process is very complex as follows:

1. Travel journey is not a linear, funnel like, decision-making process (Fig 11. Clickstream Semantic Map of One Subject). Different stages in the journey overlap and influence each other. Hence, it is hard for OTA to interfere and influence the traveler at the right stage. For example, if users are looking at a hotel list in a destination, it doesn't mean that they are ready to book a hotel, it could mean that they are just looking for a general pricing of an area to decide on a destination to go to. Hence, if specific techniques are used to make people book hotels at that stage, they won't work, since the user is not in that particular stage even though they are looking at hotels.
2. Travel is personal and contextual, depending on many factors: age, length of trip, number of trips taken, travel party composition, traveler persona (foodie, city explorer, beachgoer etc.), time taken to decide between destinations, trip planning motivations. (See Appendix I). Hence, appealing to every individual in its own specific scenario is a huge challenge for an OTA. For example, recommending hotels to one individual is very difficult as it's very hard to know the specific individual needs and his/her context.
3. Travel decision making is irrational. The literature analysis of the decision-making models reveals that there are decision influencing factors that are irrational, emotional based on intuitive reasoning. Previous studies (Cahyanto et al., 2016; Simon, 1972; Wattanacharoensil and La-ornual, 2019) show that irrational decisions are a result of travelers' limitation to

make an optimal decision when confronted with multiple choices, constraints and overloaded information. Hence, OTAs have issues identifying and influencing traveler's decision criteria especially if it's irrational. Since this behavior is irrational, OTAs can't collect this information from interviewing or surveying users.

This study concentrates on positioning effect as one irrational aspect identified by previous studies (Fig 14). Since 70% of travelers are booking online, the positioning effect for travel products online within different User Interfaces is key to understand by OTAs.

Further, it addresses the limitation in the literature around poisoning effect. Studies shown that there is a positioning effect in vertical layouts. Ert and Fleischer (2016) show the position effect in vertical layout while choosing a hotel to stay in. However, there is no research around positioning effect in horizontal layouts online. OTAs are presenting more and more the travel products in horizontal layouts (such as carousels). Hence, understanding the consumer impact of the horizontal layout is beneficial in order to influence customer behavior and promote products at key positions.

Thus, this study is addressing the question "Is there a positioning effect in horizontal layout and is the effect different than the vertical one?" The findings of this research will give OTAs the ability to influence the decision-making process of customers at an irrational level. Hence, OTAs will be able to promote different products (aka hotels) in certain positions in different layout. Additionally, they can help users discover specific products by showcasing them at specific position on their own sites or other sites (such as meta sites: TripAdvisor.com, Kayak.com, Trivago.com). Furthermore, this study helps OTAs to predict the impact (such as monetary) if they change their layout. Hence, if they decide to switch from showcasing their products vertically to horizontal view, then keeping the same placements of the product the same will impact the ones that will be chosen. This can have a monetary impact if such key positions contain sponsored products.

This research follows loosely the format described in Fig 1.

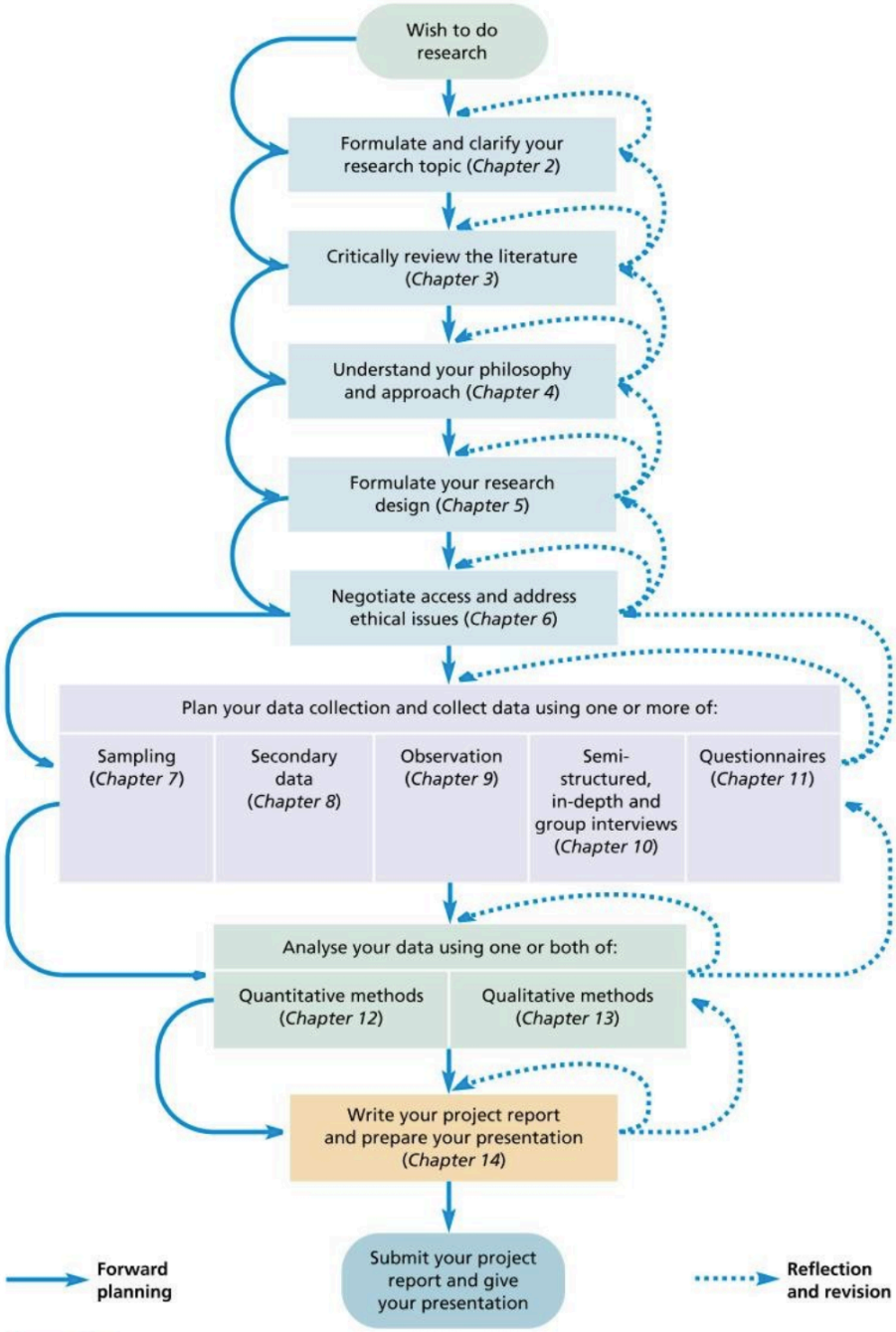


Fig 1. Research Process (Saunders et all, 2009-20012, pp:11)

First part covers the Literature Review of consumer decision making process, addressing human's limitation in making a rational decision in a complex and choice-overloaded environment. Then, it addresses the irrational decision-making process in tourism and identifies the existent heuristics at each traveler journey stage, with a focus on positioning effect.
Second part describes the research philosophy, methodology, experiment design and analysis of its results.
Last part presents the practical applications and theoretical implications of the study.

Literature Review on Traveler Decision-Making Process

Traveling is a high involvement decision as it's expensive and it happens less often. Deciding on a destination to go to, activities to do, accommodations to stay in, transportation to take is a complex decision-making process where travelers are faced with **information overload**, multiple choice options and constraints at each step in their **traveler journey**. We will review the current **decision-making models** and their limitation in including the cognitive inhibitions of humans in taking rational and optimal decision under uncertainty. Furthermore, we will uncover the irrationalities and **heuristics** that people apply, when unsure, in each of the traveler journey stage. Then we will look how **evaluation criteria** based on heuristics differs from **selection criteria** based on attributes in the decision-making process, with a focus on positioning effect heuristic.

Traveler Journey

This section will describe the traveler journey in order to underline the complexities (mainly information overload) that consumers have to face to go on a trip.

There are six critical stages to any traveler journey: inspiration, shopping, booking, pre-trip, in-trip, and post-trip. (See Fig 2) At every step, travelers will engage with travel brands for a range of services, and experience hundreds of touchpoints.

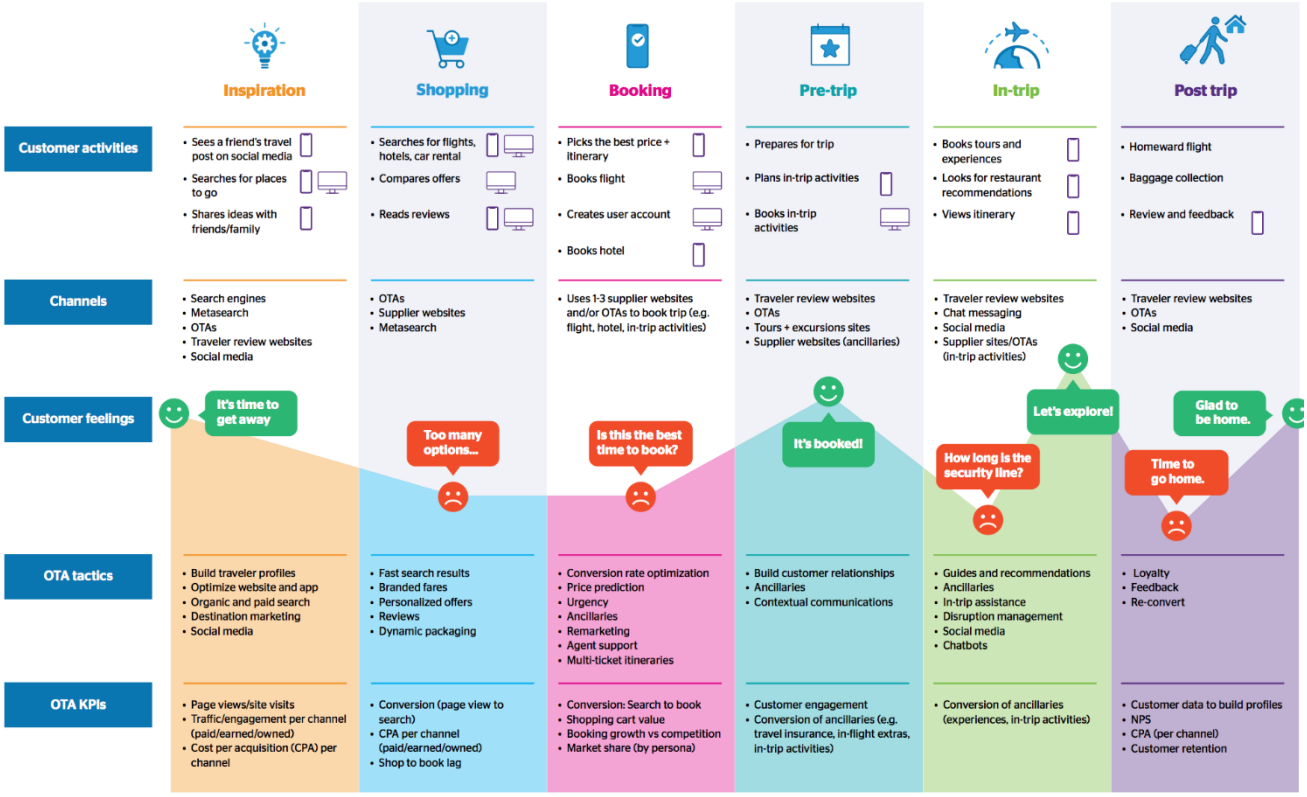
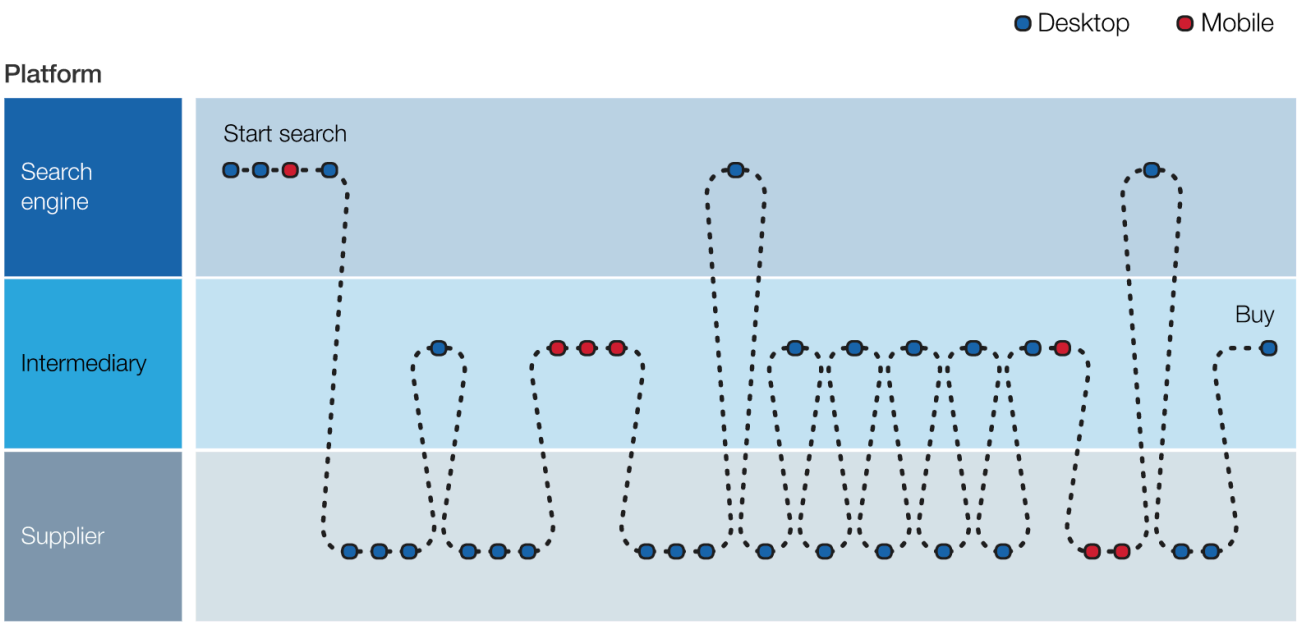


Fig 2. Traveler Journey (Travelport, 2019)

(McKinsey, 2019) suggest helping travelers by shortening and making easier their traveler journey, which currently is around 36 days long including 45 touchpoints. (Fig 3)



[1]This example shows a single journey, which happens to have 35 touchpoints. The average across our data set was 45 touchpoints.

Fig 3. Traveler Journey 45 Touchpoints. (McKinsey, 2019)

This paper will address the inspiration, shopping and booking stages of the journey, by helping people to select faster the best product for them. In order to achieve this, we will have to understand how the decision-making process works and what are the influencing factors for making decisions in environment with information overload (Appendix J).

Traveler Decision-Making Models

There is a plethora of research in decision-making models in consumer behavior.
Engel (1968) identified a logical and linear progression that an individual goes through that leads to an optimal decision

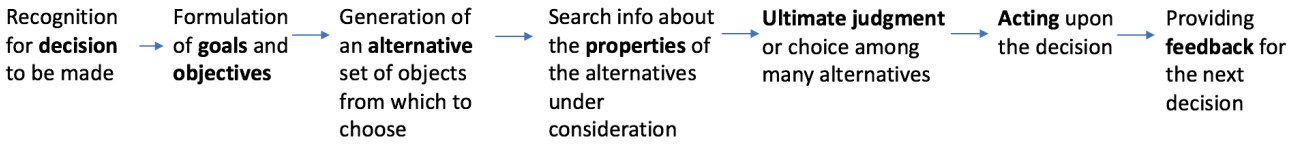


Fig 3. Linear Decision-making Process Adapted from Engel (1968)

(Degroot 2005) talks about the utility theory where the optimal decision maximizes the expected utility, a probability-weighted average of utility over all possible outcomes of a decision.

Tourism decision-making theory has borrowed from consumer behavior theories, although there are limitations in applying goods-based decision principles to experiential purchases. (Stone, 2016).

A number of travel models developed based upon consumer behavior theory have been proposed:

1. **<u>Choice Set Models or Structure Models</u>** focus on the process through which individuals reduce a large set of potential destinations to a single one (Fig 6 below). This process is linear in nature and follows the Engel (1968) model from generic consumer behavior.

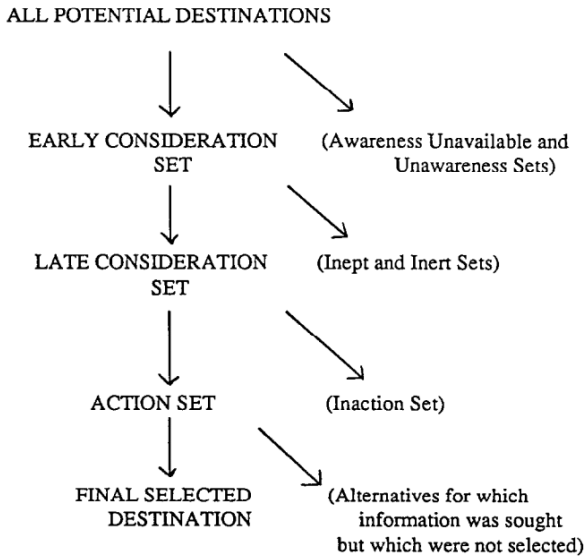


Fig 6. Choice Set Model

(Woodside and Lysonski, 1989) review of tourism decision-making research concluded that consumers are believed to follow a funnel-like process, that destination choice decisions are assumed to be sequential in nature and may be comprised of sets. The model shows 8 variables and 9 relationships; two exogenous variables, traveler characteristics and marketing variables, influence traveler destination awareness. (Fig 7 below)

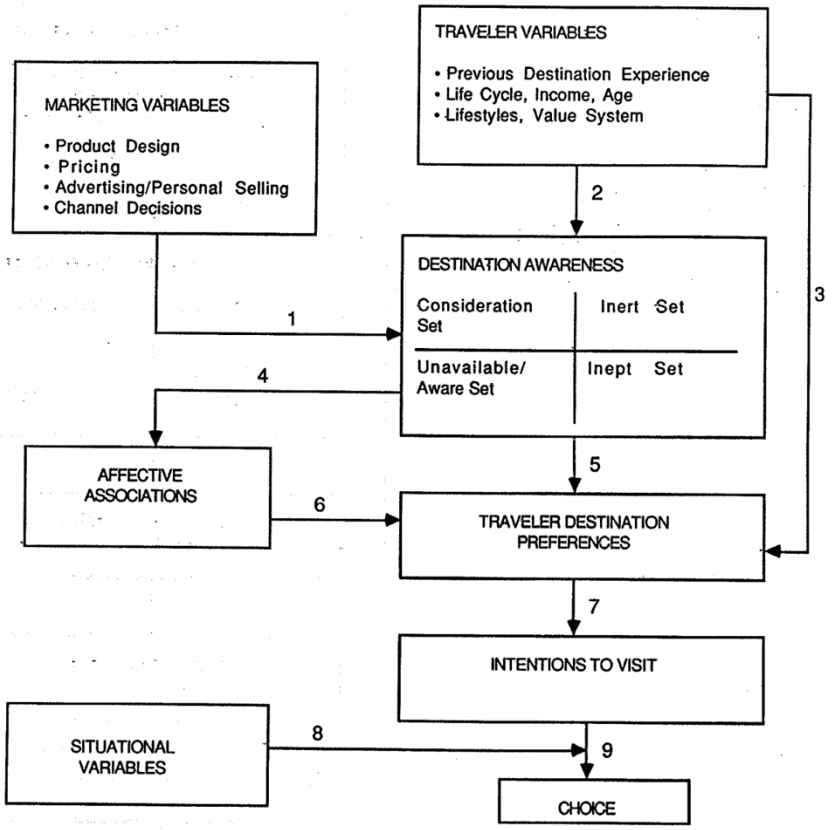


Fig 7. General Model of Traveler Leisure Destination Awareness and Choice. (Woodside and Lysonski,1989)

Structural models (Fig 5) are reductive in nature because they only deal with a small part of variables and relationships that may be involved in decision-making processes, therefore showing severe limitations for thorough understanding of tourist behavior. Inadequate attention is paid to the context of decision making (Decrop, 2006). Hence, process models were proposed to overcome this limitation.

2. **Process Models** focus on the process that travelers follow in order to identify and select a destination.

Process models differ from structural models by focusing not on the decision itself but rather on the psycho-behavioral variables that underlie decision making. Moutinho (1982) has proposed the most encompassing process model so far by making a comprehensive overview of all major variables that intervene in the tourist decision-making process. (Fig 8)

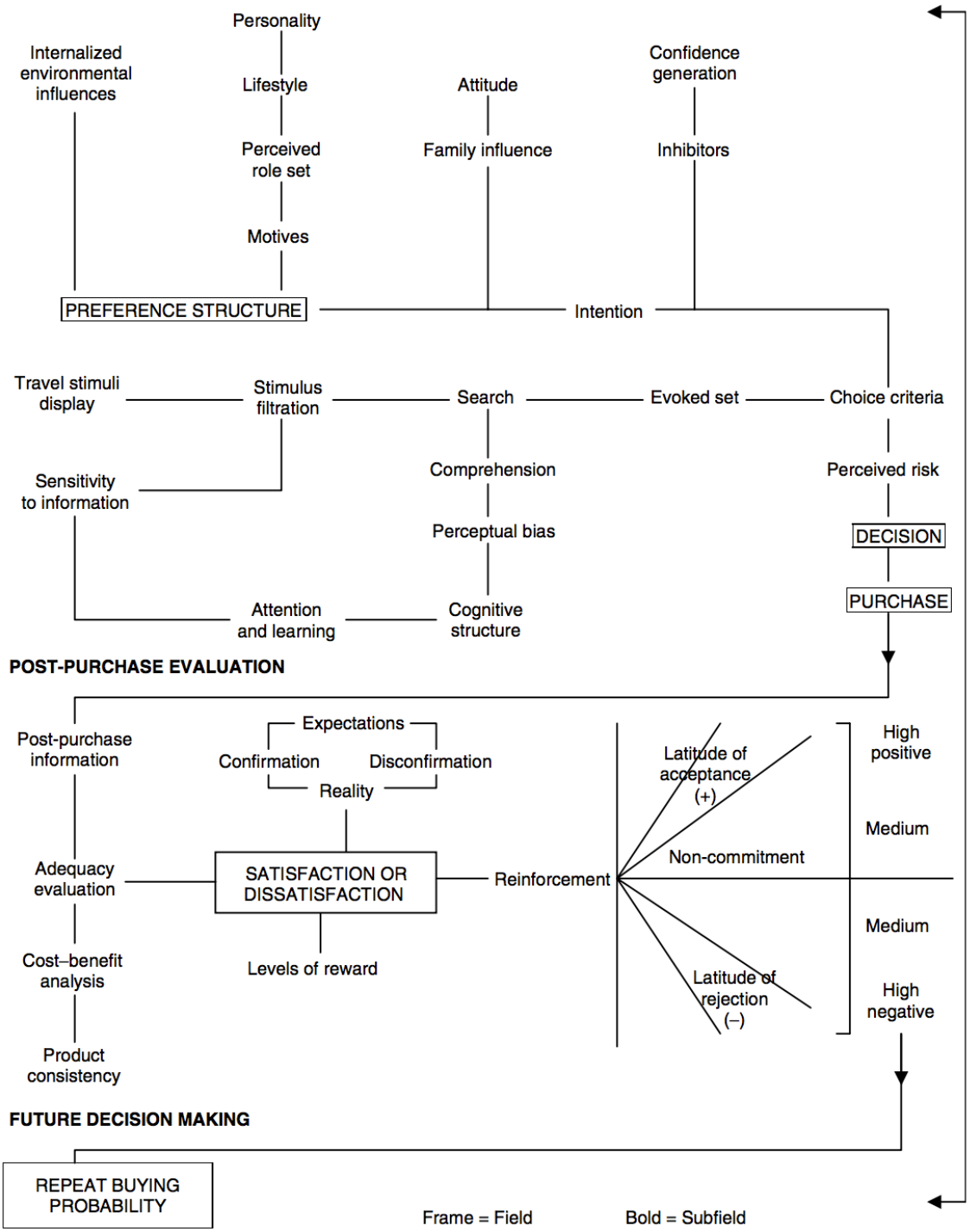


Fig 8. Vacation Tourist Behaviour Model (Decrop, 2006).

The process models have a limitation as they don't describe the interactions of decisions and behaviors of the travel party. Hence, decision net models are proposed to cover this aspect.

3. **<u>Decision Net Models</u>** examine the travel decision at an aggregate level and focus attention on the relationships between the various 'facets' of travel planning. Woodside and MacDonald develop a general system framework meant to fill the gap in what structural and process

models fail to capture: the rich interactions of decisions and behaviors of the travel party and the destination environment experienced by the travel party.

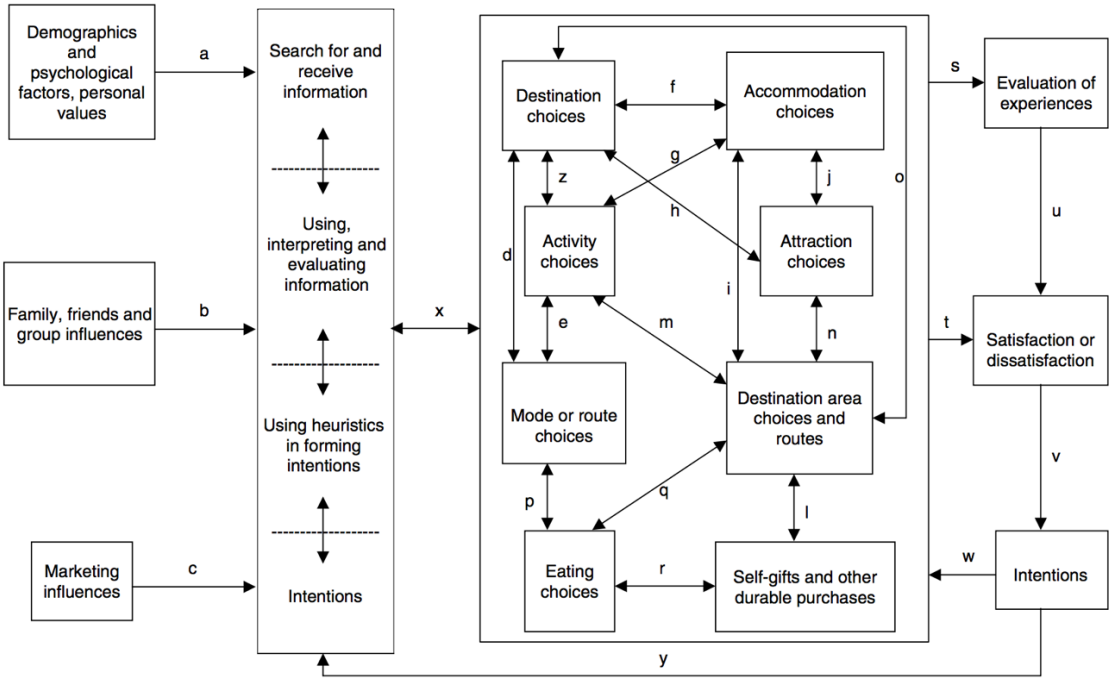


Fig 9. Woodside and MacDonald's general systems framework of customer choice decisions of tourism service. (Decrop 2006: p. 40).

In addition, (Fesenmaier et al., 2006, p.22) argue that "travel decision-making is assumed to have a net structure, implying that one sub-decision relates directly or indirectly to all other sub-decisions" and proposed a multistage hierarchical trip decision net model (Fig 10).

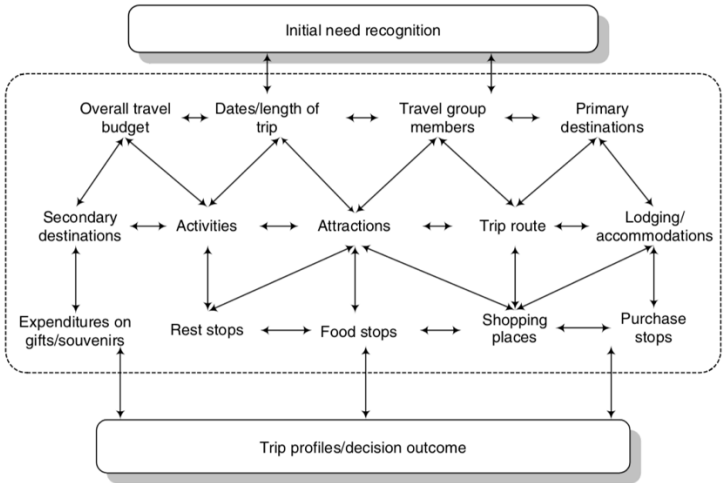


Fig 10. A decision net of tourism travel (Fesenmaier et al., 2006, p.22)

Critique and Limitations

Linearity and rationality are two aspects that can be challenged in all the models above. However, we will focus mainly on the rational factor.

Linearity

One downside of all these models is that they imply that decision making process is linear, passing from one stage to another influenced by different factors.
However, in reality the traveler decision-making process is non-linear as illustrated in Fig 11 below by monitoring online clickstreams:

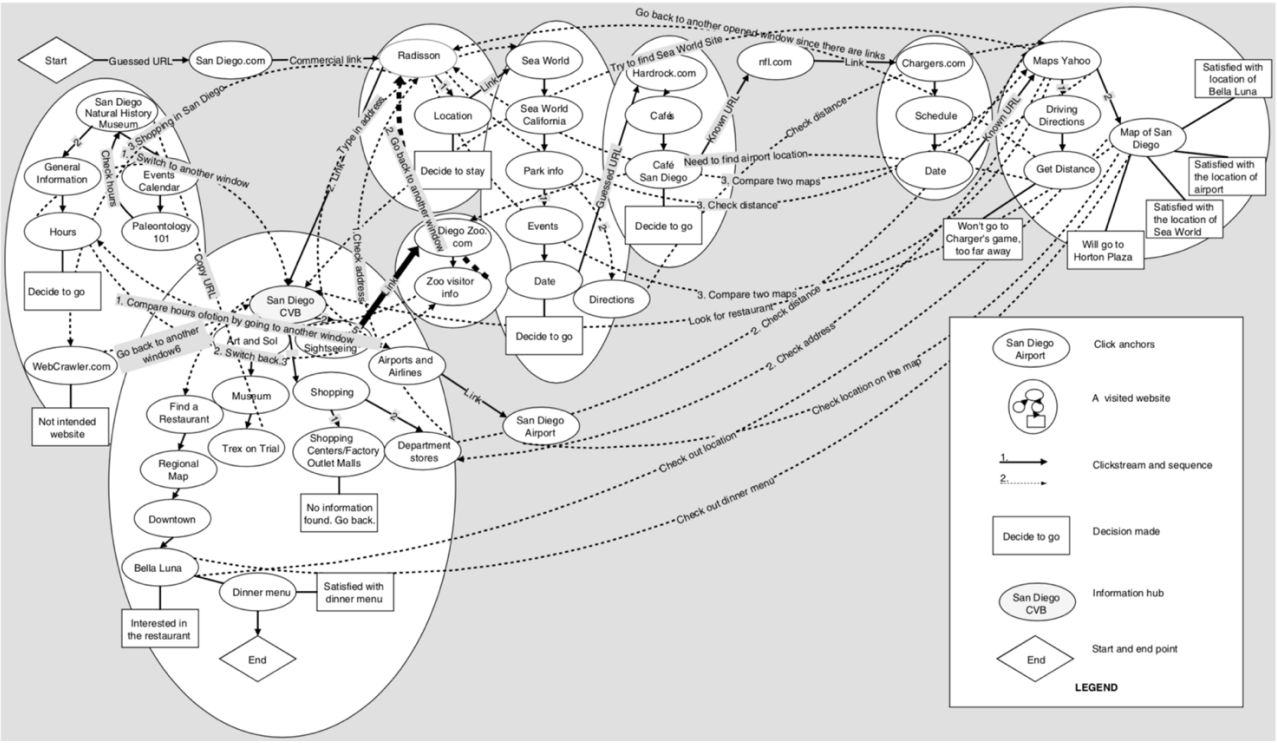


Fig 11. Clickstream Semantic Map of One Subject (Fesenmaier et al., 2006)

(Decrop and Snelders, 2004) also argues that vacation planning is not as linear or organized as previously hypothesized.

All of the decision-making models, believed that decision is happening in a funnel like progression, where the decisions are taken one after another, influenced or not but specific factors or by previous step decision (such as in the net model in Fig 10). However, first of all people don't decide in one shot, especially when dealing with high-involvement decisions. Hence, decisions can span across a longer period of time: 43% of people in US choose within a week; 34% choose within 1-4 weeks; and 21% choose between 1-5 months (Phocuswright, 2019). Knowing this fact, the consumers are starting their search in one moment in time, then abandon or booking one part of the trip or deciding on one factor, then coming back to the sites not necessarily remembering where they left of, or what decision they made the last time they were there. This process also shows that people might be in a different context and influenced by different factors every time they come back.

Rationality

Another limitation of these models is that traditional choice models based on utility maximization, rational choice, and orderly problem-solving processes may not apply to many tourism scenarios because tourism purchases are typically hedonic and experiential in nature (Decrop & Snelders, 2004). This could mean that the utility theory would be sufficient predictor of human decision. However, (Kahneman and Tversky,1979) developed "prospect theory" that asserts that, in the face of uncertainty, we group risks and then build value functions to assess them. These functions are not linear, in part, because of loss aversion; they are steeper for losses than for gains because people are more concerned about losing what they already have than gaining what they do not yet have.

Furthermore, Kahneman and Tversky observed that people do not focus on total accumulated wealth; rather, they assess their risk from a personal reference level, and that people also overweight low probability outcomes and underweight moderate to high ones. (Greenberg and Lowrie, 2012)

(Tversky & Kahneman, 1974) also talk about System 1 and System 2 (Fig 12) as two distinct modes of decision making that aligns with non-compensatory decision making (System 1) and compensatory decision making (System 2) (Appendix A: Compensatory vs. Non-Compensatory Decision Making):

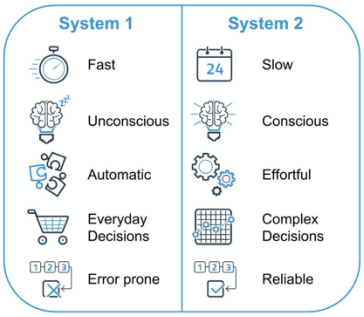


Fig 12. System 1 vs. System 2 (Upfront Analytics, 2019)

In addition, many researchers argue that travel decisions are not as rational and utilitarian:

- Decisions are spontaneous and impulsive (Smallman and Moore, 2010)
- "Rational" behavior is limited by factors such as decision-making heuristics, inertia, risk aversion, and information overload (McCabe et al., 2015)
- The role of others in a travel party, including friends and relatives, must be considered, as traveling is a social event (Gitelson and Kerstetter,1995)
- Traditional decision-making models are likely not appropriate to all situations, as making choices in tourism can be a "constraint and opportunity-driven process" (Decrop, 2010).

To sum up, these models have to include an influencing factor in the decision making that is irrational, affective/emotional, based on intuitive reasoning, adaptive characters and spontaneous acts. Human cognitive limitations also make tourists emotional and subjective (Gladwell, 2005). These limitations can drive tourists to rely more on trust and intuitive perceptions than on logical reasoning (Correia et al., 2014).

Influencing Factors in Decision-Making Models

All of the decision-making models rely on rational and irrational factors that influence the decision in order to move to the next stage in the process. This section will focus on irrational factors.

Rational

These factors can be **rational** and well determined, such as these described in Fig 13 and they participate in the decision-making process to arrive at the optimal choice.

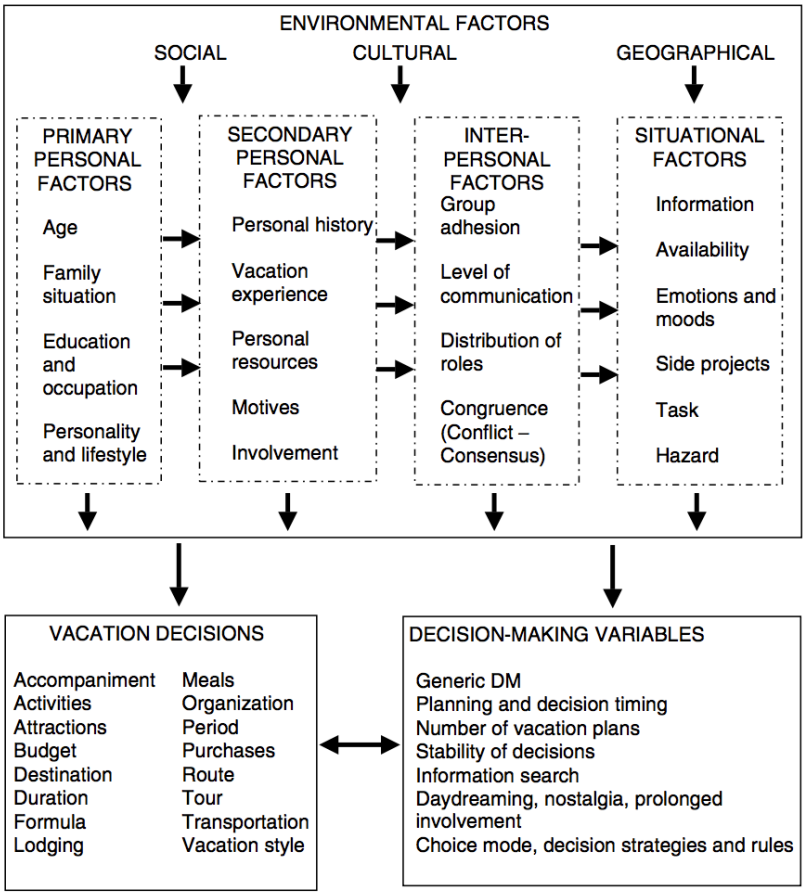


Fig 13. Factors in Vacation Decision Making. (Decrop 2006: p. 72).

Some rational decisions are taken on selecting criterion based on product attributes. The most popular attributes were discovered to be: ‘non-smoking’, ‘swimming pool’, ‘high-speed internet’, ‘hot tub’, ‘fitness center’, ‘room service’ and ‘set price range’, ‘comparison’, ‘picture’, ‘reviews’, ‘star-ratings’ and ‘sort by price’. (Jones and Chen 2011) In addition, PhocusWright (2019) survey, discovered that most of the people select a destination based on better value for money, accommodation type (3 star-hotel as being the most selected in US) follow by other destination characteristics (Fig B).

	Australia	Brazil	China	Germany	Mexico	U.K.	U.S.
Appealing accommodations	42%	39%	20%	63%	33%	45%	46%
Walkable	33%	17%	15%	19%	24%	38%	23%
Quality beaches	25%	47%	30%	33%	47%	29%	29%
Historical	21%	40%	29%	21%	23%	25%	22%
Local affordability	19%	26%	12%	21%	6%	12%	16%
Local culture	19%	19%	32%	13%	16%	16%	16%
Food and dining available	17%	10%	17%	17%	21%	15%	18%
Natural features/landscapes	15%	7%	35%	14%	11%	11%	12%
Landmarks	15%	6%	14%	7%	17%	11%	13%
Available activities	14%	12%	11%	7%	14%	8%	21%
Technological connectivity	8%	10%	9%	8%	11%	8%	7%
Shopping	7%	3%	9%	3%	6%	4%	5%

Question: Which of the following characteristics do you typically look for in a vacation destination? *Select up to three options.*
Base: Global leisure travelers who selected a destination independently: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Note: Top three for each respective market highlighted in orange
Source: *Destination Decision: How Travelers Choose Where to Go*

Fig B. Top Destination Characteristics (PhocusWright, 2019)

Irrational

However, (Decroo 2006) or any of the decision models above don't talk about the irrational factors that influence decision making process. The irrational factors are a result of the limited ability of humans to arrive at the optimal solution, which may be caused by time and cost constraints, limited cognitive capacity, and incomplete or overloaded information. People cannot often maximize the utility of all possible choices (Cahyanto et al., 2016). Instead, individuals make good decisions that are good enough, rather than optimal (Simon, 1972)

Various studies on decision making in the tourism context, incidents and prognoses of cognitive biases with regard to their types and stages where they arise are still abstruse (Fig 14. Cognitive Biases Discovered at each Travel Stage). Aspects of cognitive biases in tourist decision making are still underexamined.

However, (Wattanacharoensil and La-ornual, 2019) go over a comprehensive list of articles examine cognitive biases in tourism. They found the most frequent biases in the decision-making process for each stage in travel (Fug 14).

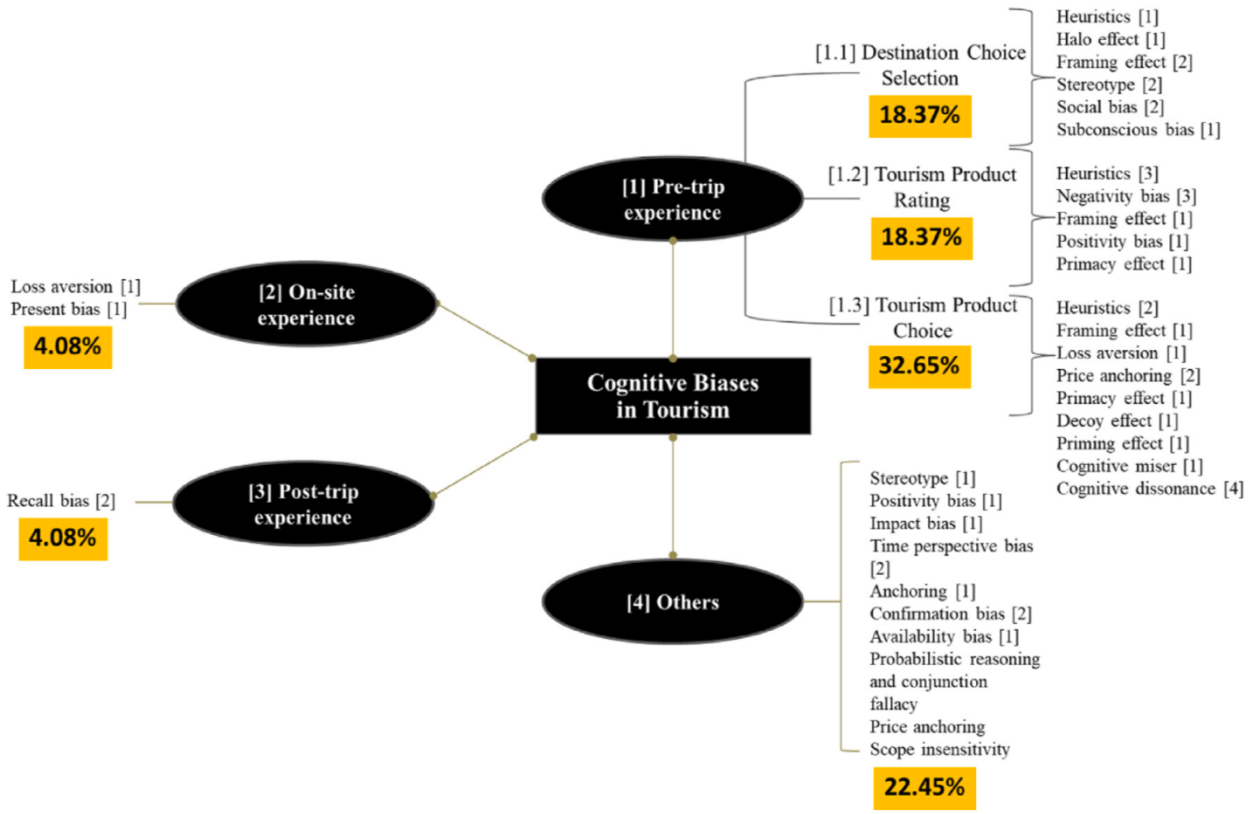


Fig 14. Cognitive Biases Discovered at each Travel Stage. (Wattanacharoensil and La-ornual, 2019)

A heuristic, or mental shortcut, is an approach to problem solving to simplify the decision-making process under uncertain and intricate conditions, a bias is a prejudice. Fig 15 goes in detail to explain each bias.

Bias types	Bias explanations	Selected article
Heuristics	… or rules of thumb, are the cognitive tools we use to simplify the decision making process (Bazerman and Moore, 2009)	Tanford and Kim (2018); Tanford et al. (2018); Park and Nicolau (2015); Castelltort and Mäder, 2010; Xiang et al. (2017); Tan, Lv, Lui, & Gusoy (2018)
Social bias	… prejudicial attitudes toward particular groups, races, sexes, or religions, including the conscious or unconscious expression of these attitudes in writing, speaking, etc.	Stepchenkova, Su, & Shichkova (2019); Gritzalls, & Stavrou (2018)
Stereotype	.. when a person has certain characteristics about another person, thing or place without having actual information…	Chen et al. (2013); Castelltort and Mäder, 2010; Berdychevsky et al. (2016)
Framing effect	… the situation when choices being made are influenced by the way they are framed. Framing effect occurs when changing perspective influences evaluation of outcomes	Tanford et al. (2018); Sparks and Browning (2011); Kapuściński and Richards, 2016; Zhang et al. (2018)
Cognitive dissonance	… the situations when attitudes, beliefs or behaviours of a person are not aligned and could create conflict and he or she can react in the irrational way in order to maintain the consonance (McLeod, 2018).	Tanford and Montgomery (2015); Park and Jang (2013); Park and Jang (2014); Tseng (2017)
Anchoring	… the tendency to anchor a decision at an initial value and fail to adjust sufficiently to reach the true value	Book et al. (2016); Tanford et al. (2018); Higham, Ellis, & Maclaurin (2019);
Negativity bias	… things of a more negative nature have a greater effect on one's psychological state and processes than neutral or positive things	Tanford and Kim (2018); Park and Nicolau (2015); Zhang et al. (2016)
Loss aversion	… changes from reference points may be valued differently depending on whether they are gains or losses and people tend to avoid potential loss and leading them to make irrational decision	Nicolau (2012); Nguyen (2016)
Positivity bias	… a pervasive tendency for people, especially those with high self-esteem, to rate positive traits as being more true	Ouyang et al. (2017); Xiang et al. (2017)
Primacy effect	… recalling or seeing primary (last) information presented better than information presented later on (before)	Ert and Fleischer (2016); Sparks and Browning (2011)
Bias on memory (Recall bias)	… bias which occurred when people remember past events that easily spring out into their memories but don't usually have a complete or accurate picture of what happened	Lee and Kyle (2012); Smith et al. (2015)
Time perspective bias	… refers to the relative focus and valence a person assigns to past, present, and future time frames.	Kah et al. (2016); Lu et al., 2016a, b
Confirmation bias	… the tendency to interpret new evidence as confirmation of one's existing beliefs or theories.	Chi et al. (2018); Higham et al, (2019)
Halo effect	… when a person making an initial evaluation of another person, place, or thing based on the assumption of ambiguous information	Kneesel et al. (2010)
Cognitive miser	… a social psychology theory that suggests that humans, valuing their mental processing resources, find different ways to save time and effort when negotiating the social world	Tanford et al. (2012)
Decoy effect	… (or attraction effect) is the phenomenon that consumers will tend to have a specific change in preference between two options when they are presented with a third option that is asymmetrically dominated	Kim et al. (2018)
Priming effect	… how ideas prompt other ideas later on without an individual's conscious awareness	Thai and Yuksel (2017)
Impact bias	… tendency that people overestimate the intensity and duration of their emotional reactions to future events	Larsen, Brun, & Ogaard (2009)
Subconscious bias	… while individuals are likely to respond better to human cues, they are unlikely to be aware of what has occurred, or why they feel more favorable towards the message they have just seen	Letheren et al. (2017)
Cognitive bias	… a systematic pattern of deviation from norm or rationality in judgment	Tan, Lv, Lui, & Gusoy (2018)
Sunk cost effect	… when a person is more likely to continue with a project if he or she has already invested a lot of money, time, or effort in it, even when continuing is not the best thing to do	Park and Jang (2014)
Present bias	… tendency of people to give stronger weight to payoffs that are close to present time when considering trade-offs between two future moments.	Nguyen (2016)
Availability bias	… the estimation of frequency or probability by the ease with which instances or associations could be brought to mind.	Higham et al, (2019)
Probabilistic reasoning and conjunction fallacy	… individuals exhibit a bias toward overestimating the probability of conjunctive events and underestimating the probability of disjunctive events	Higham et al, (2019)
Scope insensitivity	… the amount that a person is willing to pay for purchasing moral satisfaction (e.g. donation) is relatively insensitive to the actual nature and extent of harm to be ameliorated	Higham et al, (2019)

Fig 15. Detailed Explanation of each Bias Type (Wattanacharoensil and La-ornual, 2019)

This paper will focus on heuristics on positioning effect that can help with information overload.

Positioning Effect

This section will evaluate the previous studies on positioning effect online and offline in horizontal and vertical presentation. Overall, the vertical presentations were believed to have a primacy and recency effect while the horizontal ones a middle effect, with a few exceptions.

Vertical Presentation

(Ert and Fleischer, 2016) experiment resulted in a nonlinear effect of hotel position on the list of choices: hotels that were listed at the top (primacy) and bottom of the list (recency) were more likely to be chosen than those listed in the middle. The main explanation for these findings relies on the "satisficing principle" (Simon 1957), which suggests that people choosing between different alternatives conserve resources and select the most accessible satisfactory option presented, even if it is not optimal. However, the study was conducted using a vertical presentation of the 10 hotels. In addition, while **(**Ert and Fleischer, 2016) "controlled the other factors of potential relevance (e.g., hotel attributes)" this was not demonstrated or tested. Hence, the study might have been influenced by the hotel attributes preferences. The price range $144–$184 that was picked for all the 10 hotels has still a wide range. For example, a hotel at $144 might have been preferred over one at $184. In addition, there were other attributes that might have influenced the decision, such as: photo, description, facilities, policies etc. that could be seen on another web page if participants decided to sample them. This introduced noise in the experiment that wasn't explicitly accounted for in the analysis and in the results.

Most studies documenting primacy effects, recency effects, or both focus only on vertical presentations (e.g. a restaurant menu (Dayan and Bar-Hillel 2011) and ordering deliveries online (Murphy et al., 2006)). However, the restaurant menu study used only four different menu ordering, hence not all items appeared in all possible positions. (Breugelmans et al., 2007) study found a primacy effect, that is, items on the first screen were more likely to be selected, but the absolute placement of products on a screen was not influential: only their placement relative to focal items seemed to have an impact.

Horizontal Presentation

Overall, there are certain position rules that seem to govern the physical ordering of people, items, and things across contexts and domains. (Valenzuela and Raghubir, 2009) Within a store, consumers expect products located in an end-of-aisle display to be on discount (Inman et al., 1990). In a group task, observers believe that people seated in the center are the most accurate (Raghubir & Valenzuela, 2006) and influential (Taylor & Fiske, 1975). Raghubir and Valenzuela (2006) argued that this was due to people's beliefs, based on learned associations, that important people are expected to sit in the middle (e.g., the CEO in a group interviewer panel). (Feldman & Lynch, 1988) show that when pre-existing attitudes are available, relevant and easily retrieved, then attitudes are less likely to be constructed on the basis of contextual cues, such as position.

However, most of the studies on horizontal presentations were conducted offline and they documented a middle bias when choosing from several items. Examples include choices between grocery **identical** items on a supermarket shelf, toilet stalls, and maze routes (Christenfeld, 1995); highlighters and seats (Shaw et al. 2000); and even guessing the correct answer's position in multiple-choice questions (Attali and Bar-Hillel 2003). (Attali and Bar-Hillel 2003) explained the middle bias as a tendency to avoid boundaries, an edge-aversion.

(Christenfeld, 1995) concluded in supermarket shelf, toilet stalls, and maze routes studies that people choosing from an array of identical options reliably prefer the middle ones. However, some of the results could be influenced by other factors. For example, the restroom stalls could have been

impacted by the fact that the first stall was next to the door, hence, people avoided it in order to have privacy.

In addition, traditional shelf effects appear especially important when consumers are not highly involved with the purchase decision, are pressed for time, and/or face comprehensive shopping tasks. In such situations, consumers often pursue satisfactory rather than utility-maximizing purchase decisions. (Breugelmans et al., 2007)

In addition, a few studies documented the same middle effect when choosing between a variety of chewing gums (3 varieties) or a variety of pretzels (5 varieties) (Valenzuela and Raghubir 2009). Nevertheless, the number of choices were still low. As we've seen from (Jones and Chen 2011), the consideration sets are composed of 10 hotels on average, whereas choice sets average about 4. Hence, difference heuristics might apply according to the number of items in a set. Furthermore, research on vision effects using simultaneous presentation predicts that an item left of center versus the center is most noticeable (Ducrot & Pynte, 2002)

There also studies that documented different positioning effect. (Nisbett and Wilson, 1977) discovered that "last-is-best" rather than the middle in horizontal presentation. In this study, subjects were asked to consider a linear array of 4 identical pairs of stockings and the last was preferred. However, since the choices were very limited, just 4, and the products were identical, people didn't have to perform an exhausted cognitive activity to assess all 4 products to realize that they are identical. Hence, they probably scanned all 4 to realize that they are identical, and they picked the last they scanned.
In addition, (Drèze et al., 1994) also found inconclusive results when nonidentical items were placed on shelves in a supermarket. On the horizontal axis, there was no consensus on whether it is better to be located. On a vertical dimension a central location was most desirable. However, this matches with the natural resting position of the eye.

In conclusion, there are no studies that address the selection of a highly involved purchase, such as a tourism product, in a horizontal positioning where the choice set is big enough and comprises nonidentical items.

Research Question

The goal of this paper is to evaluate experimentally if there is a positioning effect in a horizontal presentation vs. vertical one, in a high-involved decision-making process selecting from a non-identical item.
Hotel booking is considered a high-involvement process because it occurs infrequently and is a relatively expensive purchase. Thus, people planning their trip tend to expend a good deal of effort on the search for a suitable hotel.

This research will contribute to the literature by addressing these three limitations:

1. There are no studies on positioning effect on choice in an **online** horizontal presentation
2. There are no studies that address the selection of a highly involved purchase, such as a tourism product, in a horizontal positioning

3. Previous study by (Ert and Fleischer, 2016) on positioning effect on choice in an online vertical presentation didn't separate the selection criteria (based on attributes) vs. evaluation criteria (based on positioning effect). Hence this study will be able to separate the two and confirm the positioning effect explicitly by using non-negative matrix factorization technique.

Furthermore, this study will show how can non-negative matrix factorization technique can be used for any other study to decompose different types of entities that interact in order to make a final outcome. For example, this technique can be applied to the other studies to separate the preferences for a product attribute vs. heuristics (such as framing, positioning, decoy effect, loss aversion etc.).

In addition, for practical applications this study can be used to promote specific products in the observed preferred positions. For example, some OTAs are now using horizontal presentation for hotel choices (Fig 16. Airbnb). Hence it will be useful to know if there is a positioning effect in this layout compare to vertical one used traditionally (Fig 17. Expedia). As a result, tourism managers might use the findings of our study to promote their travel option.

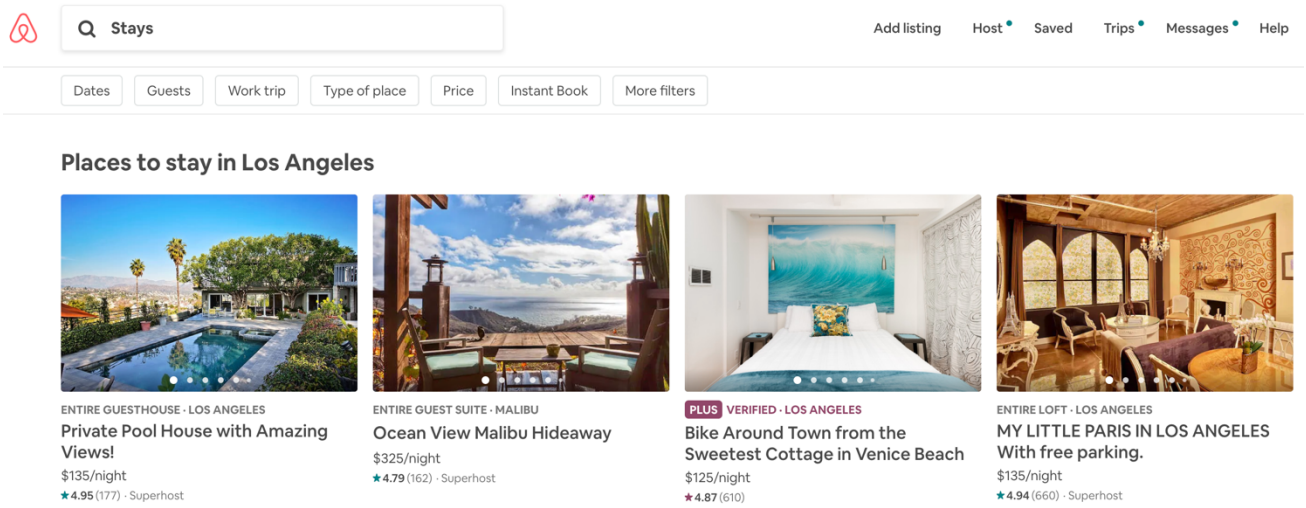


Fig 16. Airbnb.com Example of Horizontal Hotel List Layout

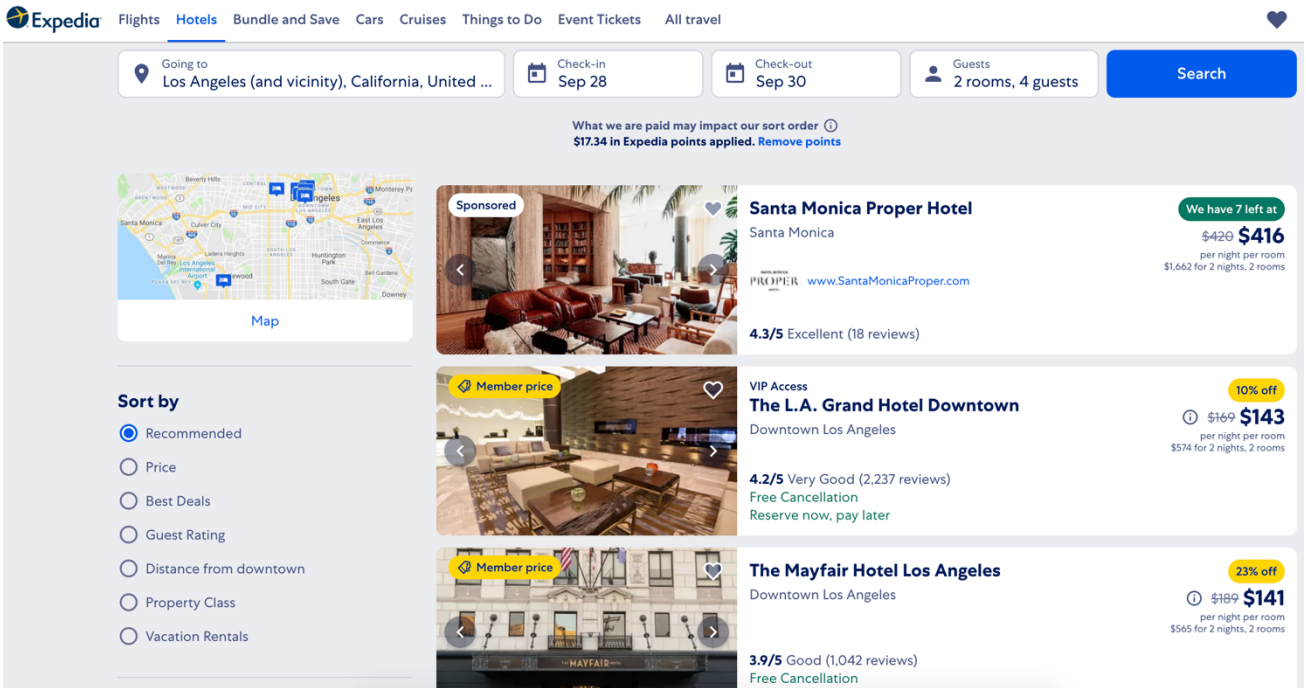


Fig 17. Expedia.com Example of Vertical Hotel List Layout

Research has found that people assign meaning to the position of an item, in the absence of alternative information. As seen in the section above, most of the findings support an advantage for items places in the middle of an array when displayed horizontally ((Christenfeld, 1995), (Shaw et al. 2000), (Attali and Bar-Hillel 2003)), with very few exceptions ((Nisbett and Wilson, 1977), (Drèze et al., 1994)). Since, the exceptions were under different conditions that the ones we test now, I will assume that they don't apply here. (Nisbett and Wilson, 1977) tested identical products and just 4 of them, while this study is testing different products and more than 4. (Drèze et al., 1994) results were in relation with shelf placement both vertical and horizontal. However, online placement is different because eye level is not considered the same way, since everything is at eye level on a web page once you scroll.

Thus, in line with traditional middle effect bias or edge-aversion from most of the studies, I expect that hotels encountered in the middle positions in a horizontal layout will receive more attention. Hence, I expect middle placements to draw substantially higher choice probability.

Therefore, this study will assess three hypotheses**:**

Hypothesis H1: Hotels displayed in the middle of a hotel list in a horizontal presentation have a higher probability of being chosen.

There could be a hybrid in decision making rules applied by a decision maker. In the book "The Nudge", Thaler and Sunstein (2009) show that as the choices become more numerous and/or vary on more dimensions, people are more likely to adopt simplified strategies (see Heuristics X Used in Fig 13). One strategy is **elimination by aspects** from the consideration set, where the decider chooses one aspect that is important, establishes a cutoff level, then eliminates all the alternatives that do not

come up to the standards. The process is repeated, attribute by attribute. The process is repeated until the set is narrow enough (choice set) to switch over to **compensatory evaluation** of the finalists see Heuristics Y Used in Fig 13). (Appendix A: Compensatory vs. Non-Compensatory Decision Making). This theory has received support from a recent empirical study (Jones and Chen 2011), which found that hotel consideration sets are composed of 10 hotels on average, whereas choice sets average about 4.

(Jones and Chen 2011) study also argues that there should be a distinction made between evaluative criteria (Heuristics X and Y in Fig 13) and choice criteria (Attributes A and B in Fig 13). Most studies established the attributes and their importance that consumers take into account in their choice criteria. In addition, Gensch (1987) found that consumers used different attributes at different stages of the choice process as portrayed in the Fig 18 below, where Attributes A applied at one stage could be different than attribute B applied at another stage. The most popular attributes in forming the consideration set were discovered to be: 'non-smoking', 'swimming pool', 'high-speed internet', 'hot tub', 'fitness center', 'room service' and 'set price range'. While the most popular attributes in forming the choice-set are totally different: 'comparison', 'picture', 'reviews', 'star-ratings' and 'sort by price'. (Jones and Chen 2011)

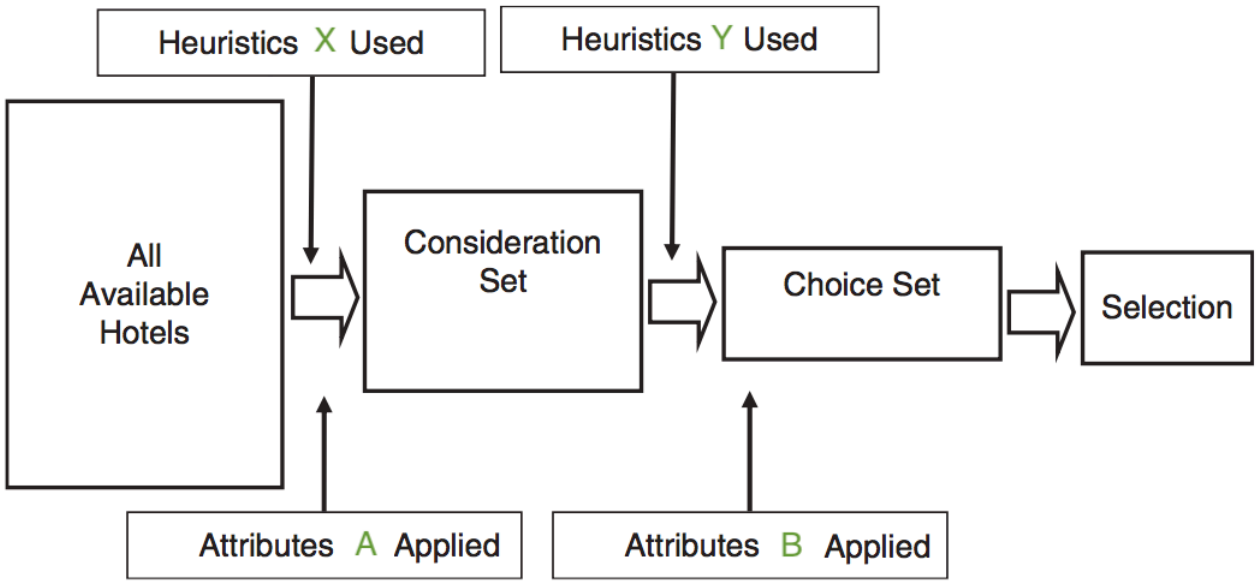


Fig 18. Adapted conceptual map of key construct (Jones et al., 2011) Legend: Green color represents the contribution brought by this paper as observed by several studies mentioned above.

(Jones and Chen 2011) study has a limitation around evaluative criteria based on heuristics unrelated to the choice criteria based on attributes. In other words, the selection criteria are based on assessing attributes (different ones for each stage) either through elimination process or compensatory evaluation. However, there can be evaluative criteria applied in the same time as choice one by applying heuristics such as positioning (primacy, recency, saliency effect etc.). They both can contribute to the final choice.

Hypothesis H2: Both choice criteria (based on attributes) and evaluative criteria (based on non-attribute heuristics) are present decision-making process and they both influence the consumer choice.

Traditional research also showed that there was a difference in customer preference depending whether the layout was horizontal vs. vertical (middle effect vs. primacy & recency effect). Primacy and recency effects were demonstrated by hotel list in **(**Ert and Fleischer, 2016) study, restaurant menu choice by (Dayan and Bar-Hillel, 2011), shelf placement (Breugelmans et al., 2007). (Drèze et al., 1994) results for placing products on the shelf showed differences between vertical vs. horizontal positioning: "On the horizontal axis, there was no consensus on whether it is better to be located on the edges or in the center of a set; half of the categories favored the edges, the other half favored the center. The results for the vertical dimension were more consistent. A central location is most desirable."

Therefore, I assume that online layouts follow the same principle. Hence, vertical and horizontal layouts will produce different choice preferences for the customers based on evaluating their positions. However, the selection criteria based on attributes should be similar for both layouts. Hence, the hotel preferences should be the same in both vertical and horizontal layouts.

Hypothesis H3: Hotels positions in a horizontal layout have a different probability of being preferred than those in a vertical layout. Meanwhile, hotels preferences based on attributes are the same in vertical and horizontal layouts.

Project Methodology & Design

This research uses a positivism philosophy, using an experiment strategy to test the hypothesis deducted from the theory review.

Research Philosophy and Approach

The research onion (Fig 19) illustrates the stages that must be covered when developing a research strategy, where each layer of the onion describes a more detailed stage of the research process (Saunders et al., 2007).

In this study we adopted a positivism philosophy that is based on the idea that scientific knowledge is the true or acceptable knowledge of the world and is characterized by the testing of the hypotheses (or research questions) derived from the existing theory of knowledge. (Newman, 1998) This is in contrast with the interpretivism philosophy that "rests on the assumption that social reality is in our minds and is subjective and multiple. Therefore, social reality is affected by the act of investigating it." (Collis Hussey, 2014) (See Appendix G for more details)

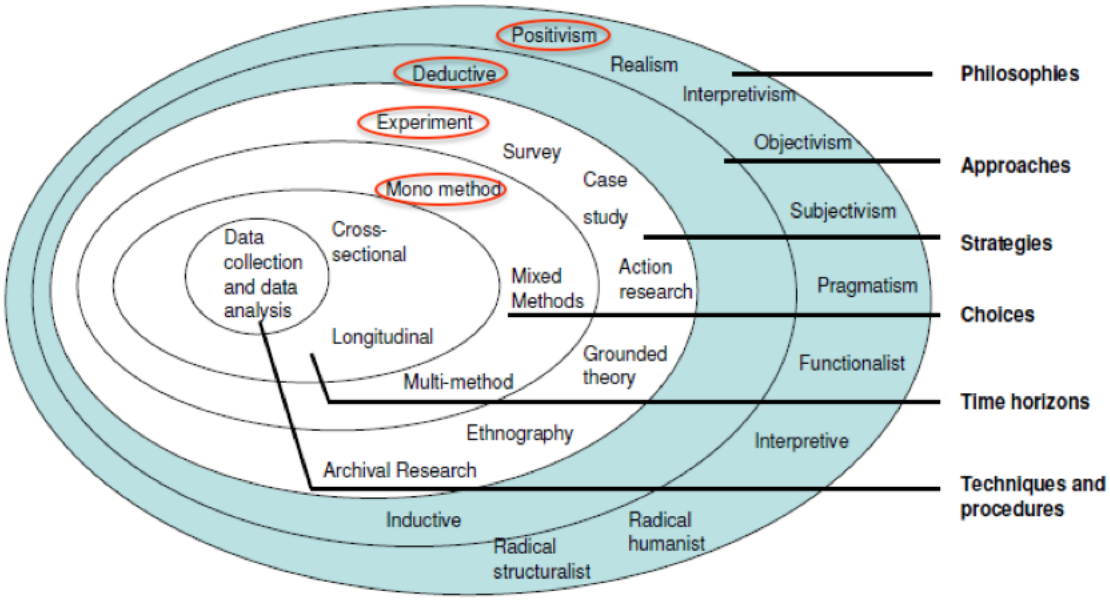


Fig 19. Research philosophy, approach, strategy and method (Saunders et all, 2009-20012, pp:11)

A deductive approach was used to formulate the three hypotheses, based on the previous studies from the literature. We will use a quantitative methodology in order to produce precise, objective, reliable results by using a large sample size. Different experiments will be used to test the hypotheses. We didn't use surveys or other type of studies due to the fact that we are testing a heuristic that people might not be aware of. Hence, if people are asked in a study if positions impacted their choice they might not answer objectively. In conclusion, the best reliable approach is to use an experiment where we can statistically analyze the consumer behavior without asking them.

Data Collection and Ethics

This research uses primary and secondary data. Secondary data, such as heuristics list at each traveler journey stage and existing studies around positioning effect in vertical and horizontal layouts, helped to inform the hypotheses. While primary data, such as the online experiments, are being used to test the hypothesis. The experiments will use an online panel service, called MTurk or Amazon Mechanical Turk. (See Appendix H)

"Ethical concerns are greatest where research involves human participants, irrespective of whether the research is conducted person-to-person." (Saunders et al, 2012, pp:208)
University of Bradford Research Ethic Committee approved the proposed research. In the proposal, we also wanted to do an interview with participants to understand their decision making, however, this was dropped due to the fact that people are not aware of the applied heuristics. Hence, asking about them won't produce valuable and reliable results. Hence, this research will use just experimental processes to test the hypotheses and contribute to the research question. Since, it uses MTurk the participants are randomly assigned to the experiment and anonymous. They are also not vulnerable as they are not related in any ways with OTAs. Participants are also reliable as their approval rate is higher than 95%. In addition, all 10000 participants are from US participating in the online panel. Each of the participant is paid 7cents per response and they have the freedom to choose the complete the task before they see it, based on remuneration and estimated time (5 minutes). Furthermore, this project is not sponsored by any of the OTAs or any travel related businesses.

Non-Negative Matrix Factorization

Matrix factorization model was chosen to calculate the probability of hotels being chosen based on positions or other preferences (attributes). Matrix factorization techniques are usually effective in these cases because they allow us to discover the latent features underlying the interactions between two different kinds of entities. Matrix factorization is to find out two (or more) matrices such that when you multiply them you will get back the original matrix. (QuuxLabs, 2010) Non-negative matrix factorization (NMF) has previously been shown to be a useful decomposition for multivariate data.

"Non-negative matrix factorization (NMF) Given a non-negative matrix V, find non-negative matrix factors Wand H such that:

$$V \sim WH \quad (1)$$

NMF can be applied to the statistical analysis of multivariate data in the following manner. Given a set of multivariate n-dimensional data vectors, the vectors are placed in the columns of an n x m matrix V where m is the number of examples in the data set. This matrix is then approximately factorized into an n x r matrix Wand an r x m matrix H. Usually r is chosen to be smaller than nor m, so that Wand H are smaller than the original matrix V. This results in a compressed version of the original data matrix. "(Lee, D. and Seung S., 2001).

Research Design for Hypothesis H1

Hypothesis H1: Hotels displayed in the middle of a hotel list in a horizontal presentation have a higher probability of being chosen

For testing the Hypothesis H1, I conducted a controlled experiment to determine if there is a causal relationship between position and hotel choice in a horizontal layout. The experiment had participants from an online panel, to choose a hotel for a trip in Tel Aviv, from a list of 10 hotels. The hotels positions in the list changed 10 times in order to determine if people have a preference for the hotel's attributes or for the actual position in the list.

Participants

Choosing a sample size to be representative of the entire US population (approx. 330milions) has to be more than 384 with a confidence level of 95% (Fig 20). However, **(**Ert and Fleischer, 2016) study on vertical positioning had 858 participants. Therefore, if we take a sample size of 1000 it is representative for a 330 million population with a margin error between 2.5-3.5% (Fig 20).

Population	Sample size
10	10
100	80
200	132
300	169
400	196
500	217
700	248
1,000	278
2,000	322
3,000	341
4,000	351
5,000	357
7,000	364
10,000	370
20,000	377
50,000	381
75,000	382
≥1,000,000	384

Source: Adapted from Krejcie and Morgan (1970, p. 608), with permission of SAGE Publications.

Required Sample Size†

Population Size	Confidence = 95% Margin of Error				Confidence = 99% Margin of Error			
	5.0%	3.5%	2.5%	1.0%	5.0%	3.5%	2.5%	1.0%
10	10	10	10	10	10	10	10	10
20	19	20	20	20	19	20	20	20
30	28	29	29	30	29	29	30	30
50	44	47	48	50	47	48	49	50
75	63	69	72	74	67	71	73	75
100	80	89	94	99	87	93	96	99
150	108	126	137	148	122	135	142	149
200	132	160	177	196	154	174	186	198
250	152	190	215	244	182	211	229	246
300	169	217	251	291	207	246	270	295
400	196	265	318	384	250	309	348	391
500	217	306	377	475	285	365	421	485
600	234	340	432	565	315	416	490	579
700	248	370	481	653	341	462	554	672
800	260	396	526	739	363	503	615	763
1,000	278	440	606	906	399	575	727	943
1,200	291	474	674	1067	427	636	827	1119
1,500	306	515	759	1297	460	712	959	1376
2,000	322	563	869	1655	498	808	1141	1785
2,500	333	597	952	1984	524	879	1288	2173
3,500	346	641	1068	2565	558	977	1510	2890
5,000	357	678	1176	3288	586	1066	1734	3842
7,500	365	710	1275	4211	610	1147	1960	5165
10,000	370	727	1332	4899	622	1193	2098	6239
25,000	378	760	1448	6939	646	1285	2399	9972
50,000	381	772	1491	8056	655	1318	2520	12455
75,000	382	776	1506	8514	658	1330	2563	13583
100,000	383	778	1513	8762	659	1336	2585	14227
250,000	384	782	1527	9248	662	1347	2626	15555
500,000	384	783	1532	9423	663	1350	2640	16055
1,000,000	384	783	1534	9512	663	1352	2647	16317
2,500,000	384	784	1536	9567	663	1353	2651	16478
10,000,000	384	784	1536	9594	663	1354	2653	16560
100,000,000	384	784	1537	9603	663	1354	2654	16584
300,000,000	384	784	1537	9603	663	1354	2654	16586

† Copyright. The Research Advisors (2006). All rights reserved.

Fig 20. Determining sample size for a given population. Left (Collis Hussey, 2014) and Right (Research Advisors, 2019)

Hence, 1000 adults from US with an approval rate higher than 95% on Amazon Mechanical Turk were assigned to the experiment. Participants were randomly assigned to one of the 10 experimental conditions to make 100 participants per experimental condition.

Task

The main task for the participants was to choose **only** one hotel from a list of 10. First, they were asked to imagine that they have planned a week-long trip to Tel Aviv with another adult. We mentioned a trip with another adult in order to make the task as a high-involvement one, as their reputation could be at stake in front of the other traveler.

Hotel List

OTAs typically present hotels in lists, typically more than 10, depending if filters were applied or not. Thai and Yuksel (2017) found that a size of 3 choices gave higher satisfaction and more certainty of the choice made than choosing from a set of 7. Park and Jang (2013) said that having more than 22 choices increased the likelihood of making 'no choice' or having regret after making a choice.

Given the info above, and not having too many or too less choices and taking into account **(**Ert and Fleischer, 2016) experiment, I took a list of 10 choices. 10 hotels from Tel Aviv were picked. I used Hotels.com site and design the selection page in order to mimic a genuine OTA website experience. (Appendix B)

Hotel Attributes

As previously mentioned, attributes contribute to determine the selection of the hotel in choice criteria (Fig 21). In this study while trying to uncover if there are other heuristics not based on attributes for hotel choice, key attributes need to be kept in order for the choice to take place.

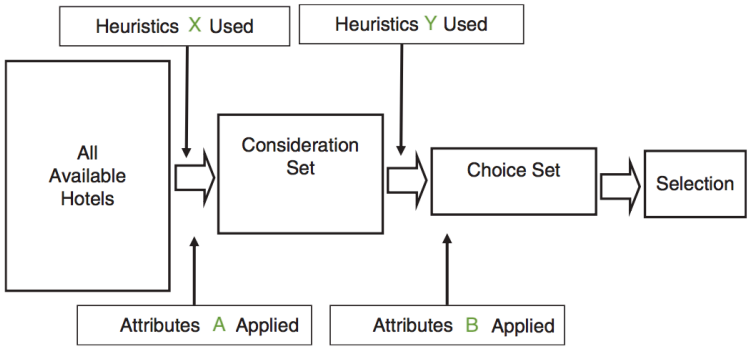


Fig 21. Attributes and Heuristics

First, I **limited** hotels' attributes by keeping only the most popular ones that were identified by (Jones and Chen 2011) as key influencers in arriving at a choice set (Fig 22):

- Hotel Name
- Hotel Image
- User Rating
- Price
- Discount

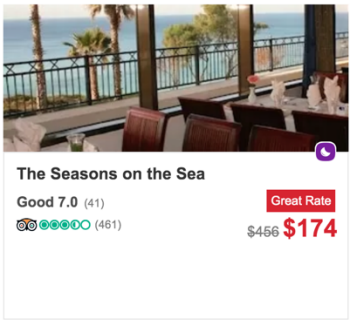


Fig 22. Hotel Design and Attributes

Second, I restricted attributes imbalance (on price and ratings), while still keeping it realistic. In addition, I filtered hotels that might stand out (See all hotel list in Appendix B):

- Hotel Names: I removed all the famous brands (hotel chains such as Marriott, Hilton, Sheraton etc.). This way I reduce the risk of people choosing a hotel due to brand awareness that plays a role in forming a consideration set.
- Images: all images were similar by having all of them depicting outdoors swimming pools or beach front
- Ratings: all ratings are between Good (7) – Superb (9)
- Prices: all hotel prices are between $168-$198
- Discount from: all discounted rates are between $269-$609

Horizontal Layout

Participants were presented with a list of hotels in a **horizontal** layout where they could scroll left and right to see all the hotels (Fig 23).

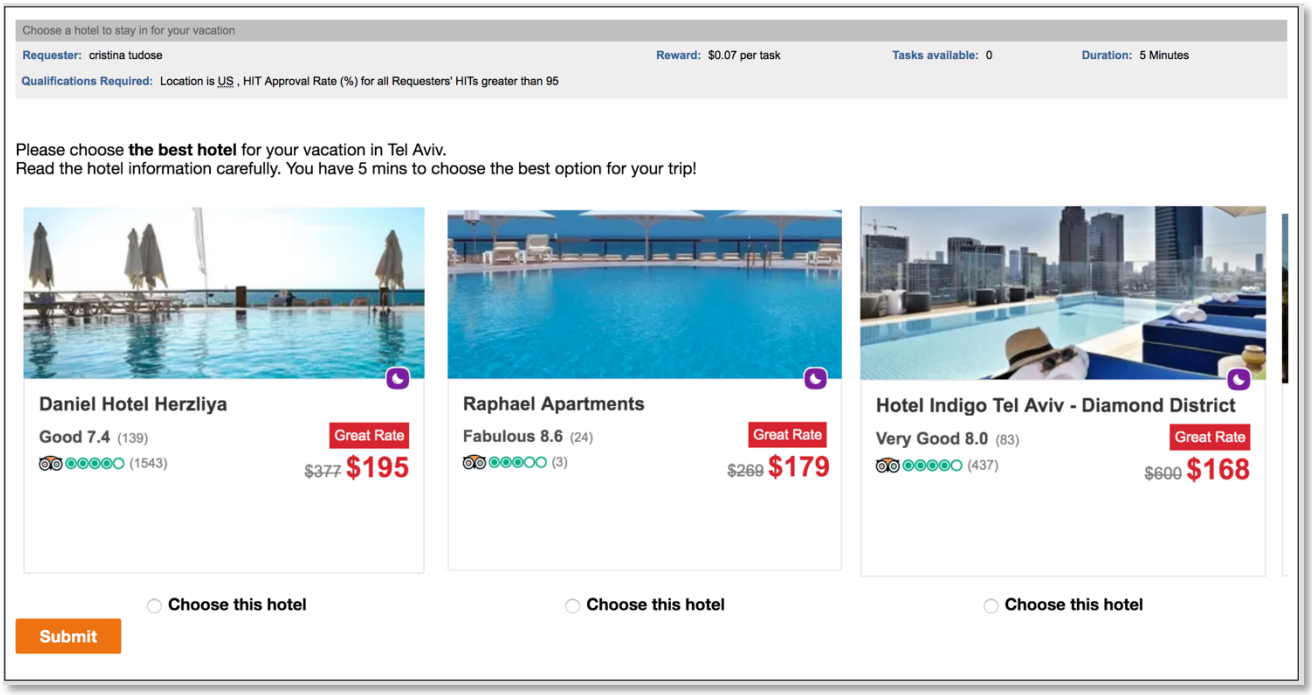


Fig 23. Screenshot of the Experiment for Horizontal Layout

Hotels Positions

An experiment was set where the 10 hotels with their respective attributes were presented in a **horizontal** layout. The study included 10 experimental conditions where the only difference between them was the hotel order/position in the list. As delineated in Fig 24, each hotel appeared once in each of the 10 possible positions.

Hotel	Cond. 1	Cond. 2	Cond. 3	Cond. 4	Cond. 5	Cond. 6	Cond. 7	Cond. 8	Cond. 9	Cond. 10
A	1	10	7	4	8	3	9	2	5	6
B	2	9	8	3	1	10	6	5	7	4
C	3	8	9	2	4	7	5	6	1	10
D	4	7	10	1	5	6	2	9	8	3
E	5	6	1	10	9	2	8	3	4	7
F	6	5	2	9	10	1	7	4	3	8
G	7	4	3	8	2	9	10	1	6	5
H	8	3	4	7	6	5	1	10	2	9
I	9	2	5	6	3	8	4	7	10	1
J	10	1	6	5	7	4	3	8	9	2

Fig 24. Hotel order/position under each of the 10 experimental conditions (based on (Ert and Fleischer, 2016) experiment within vertical layout)

Participants were randomly assigned to one of the 10 conditions where they were asked to choose one hotel. (See Appendix B for Instruction)

Results for Hypothesis H1

Each of the 10 experimental conditions had 100 answers (hotel choices) by different individuals. In addition, the answers that took less than 10 seconds were rejected in order not to skew the results by taking into account random choices. (See Appendix C: Invalid Answers) However, the experiment was resubmitted until 100 people accomplished the task for each experimental condition. In this way there was the same number of people and valid answers, 100, in each experimental condition.

Fig 25 display the results of the hotel choices and their respective positions.

	Positions:									
Hotels:	1	2	3	4	5	6	7	8	9	10
A	7	12	16	5	7	4	1	1	9	3
B	16	12	16	3	4	2	4	0	4	7
C	21	24	25	14	21	13	12	10	8	13
D	12	12	7	5	4	1	3	7	4	4
E	5	7	6	2	4	2	1	1	2	1
F	3	12	8	3	3	3	3	2	1	0
G	7	5	10	3	3	0	3	2	2	1
H	34	21	29	16	12	13	12	13	7	8
I	30	15	14	10	11	9	5	4	4	5
J	34	50	40	35	25	24	24	32	22	23

Fig 25. Horizontal Layout – Hotel Choices for each Experimental Condition

A quick analysis shows that some hotels were **preferred**, C, H and J, regardless of their position.

All the answers from Fig 25 can be represented in a 10X10 matrix. Using the non-negative matrix factorization technique, this will be the original matrix. Hence, the task is to predict the latent features in the consumer choice: positions vs. hotel preference based on attributes. Hence, the result would be 2 matrices that multiplied will have to result in the original one.

Appendix D contains the implementation of the algorithm in Python for running the experiment results. Below in Fig 26 are the results of the two matrices:

	A	B	C	D	E	F	G	H	I	J	K
Hotels Preference	A	B	C	D	E	F	G	H	J		
Horizontal	6.39	7.06	**14.98**	5.8	3.16	3.98	3.72	**16.05**	10.7		
Positions Preference	A	B	C	D	E	F	G	H	J		
Horizontal	14.64	15.64	14.88	10.11	8.84	7.5	7.14	8.28	6.18		

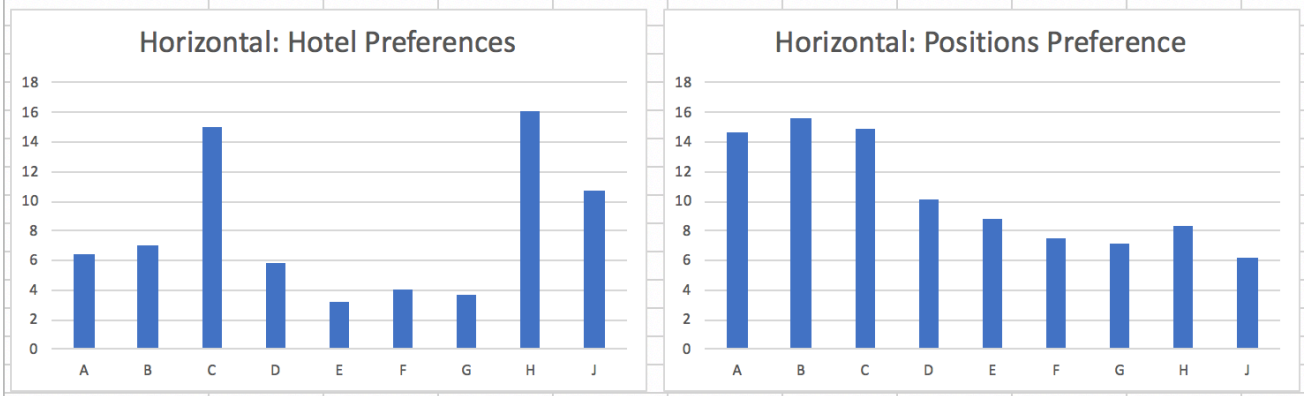


Fig 26. Preferred Hotels and Positions in Horizontal Layout

Based on the results we clearly see the preferred hotels C, H, J. However, we also see that there is a preference for the **first 3 positions** in the list.

In conclusion, hypothesis H1 is refuted as the people are most likely to choose the first positions in a horizontal layout and **not** the middle.

Discussion and Applications for Hypothesis H1

Positioning Effect

The results show that hotel position on a web page in a horizontal layout significantly influences the choice of hotel even higher than in a vertical layout (Fig 32. Position Preference Comparison).
The hotels located at the beginning of the list were more likely to be chosen than hotels positioned further away.
An explanation can be that primacy and satisficing principle are exercised in the horizontal layout more so than in the vertical layout. This refutes the hypothesis H1 where the middle effect was observed (e.g. identical items on a shelf; identical toilet stalls, multiple choice questions tests).
Another explanation of the different results could be that the current study, in comparison with the previous ones, is the first one to examine a position effect in a horizontal presentation for a high-involvement decision, like booking a hotel. Hence, when consumers are faced to make a high involvement decision, they might behave different than when the choice doesn't matter that much: picking a hotel for a vacation for a week vs. picking a chewing gum or a pretzel (Valenzuela and Raghubir 2009).

Application

The results of this research provide some empirical evidence of a "nudging" processing in the travel domains. The concept of nudge has been suggested by Thaler and Sunstein (2009), showing the importance of simple cues on behavioral change. For example, a simple change of display location can significantly change food consumption behavior (Keller et all, 2015); preference for a healthy snack option can be higher when the healthy food option is placed in the middle (vs. on the edge) of a list.
Similarly, based on our study, OTAs can promote different hotels to the top of the list in a horizontal layout.
In addition, this study is important for meta sites like TripAdvisor, Kayak, Trivago who aim to give a fair chance to competing brands. These sites have to take into account the position of the hotels promoted by several brands and optimize it with respect of the goals they want to achieve. For example, if they want to promote specific brand names, they can utilize the positions in question. Otherwise, if they want to give equal chance to all the competing brands, they should randomize their listings all the time.

Research Design for Hypothesis H2

Hypothesis H2: Both choice criteria (based on attributes) and evaluative criteria (based on non-attribute heuristics) are present decision-making process and they both influence the consumer choice.

For testing Hypothesis H2, I used the same experiment as for H1, the only difference being on the analysis of the results.

Results for Hypothesis H2

Based on Fig 26, hypothesis H2 is accepted since both:

- Choice criteria based on hotel attributes and
- Evaluative criteria based on non-attribute heuristics, positioning

are impacting the decision-making process of selection a hotel in a horizontal layout.

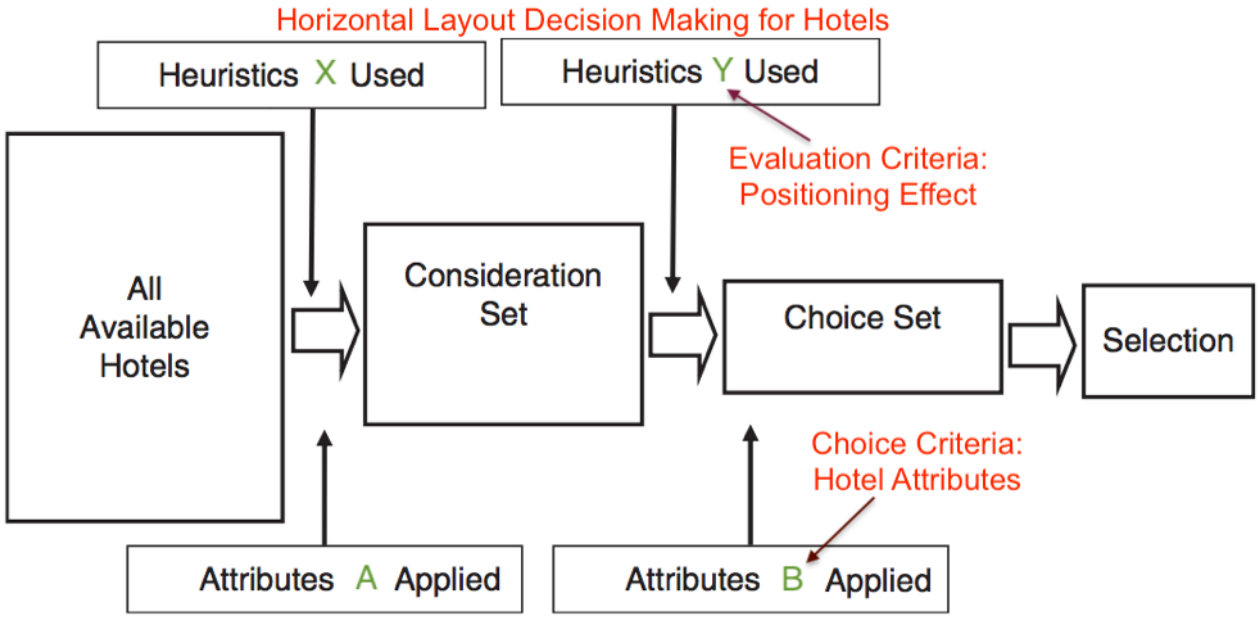


Fig 27. Evaluation and Choice Criteria Applied for Hotel Choice in Horizontal Layout.

Even though the positioning effect exists, we demonstrated that hotel selection based on its attributes plays a role in the final selection in a horizontal layout.

Discussion and Applications for Hypothesis H2

Choice Criteria vs. Evaluation Criteria

Since hotels attributes have an important weight in the decision-making, OTAs should continue to focus on emphasizing the attributes that matter to the choice criteria in each stage of the decision making. Furthermore, OTAs should also focus on heuristics that are based on attributes, such as "framing effect", "social bias", "anchoring" (on price), "loss aversion", "negativity and positivity bias" etc.
In addition, knowing that the last positions are the least likely to be chosen in horizontal presentation, if OTAs want to promote the last positions they should somehow draw attention to those positions by using heuristics based on attributes.

Other interesting application in tourism could be in choosing destinations to go to, locations, activities, like things to do (see Fig 34 Google example)

Other Applications

Knowing that attributes-based decision matter alongside with non-based attributes heuristics, OTAs can utilize both in order to develop world class recommendations. In order to combine both, OTAs ca have one recommendation system based on attributes. There are several recommendation techniques (Appendix F) within artificial intelligence realm but they are out of scope for this paper. However, the aspect that is not taken into account in these models is the irrational aspect of the decision-making process.
Hence, if OTAs combine both the machine learning recommendation techniques with the heuristics on positioning, they will determine the right place and the right hotels to recommend to users. Hence, not only influence them in their decision but also shortening the time to search for options. In this way the most optimum option will be presented based on specific attributes and also in the right position (at the beginning in a horizontal layout).

Research Design for Hypothesis H3

Hypothesis H3: Hotels positions in a horizontal layout have a different probability of being preferred than those in a vertical layout. Meanwhile, hotels preferences based on attributes are the same in vertical and horizontal layouts.

For testing Hypothesis H3, I ran the same experiment as above, in a vertical layout to assess if there are any differences and also validate if **(**Ert and Fleischer, 2016) findings can be reproduced with other type of hotels.

Vertical Layout

For Hypothesis H3, participants were presented with the exact same list of hotels but in a **vertical** layout where they could scroll up and down to see all of them (Fig 28).

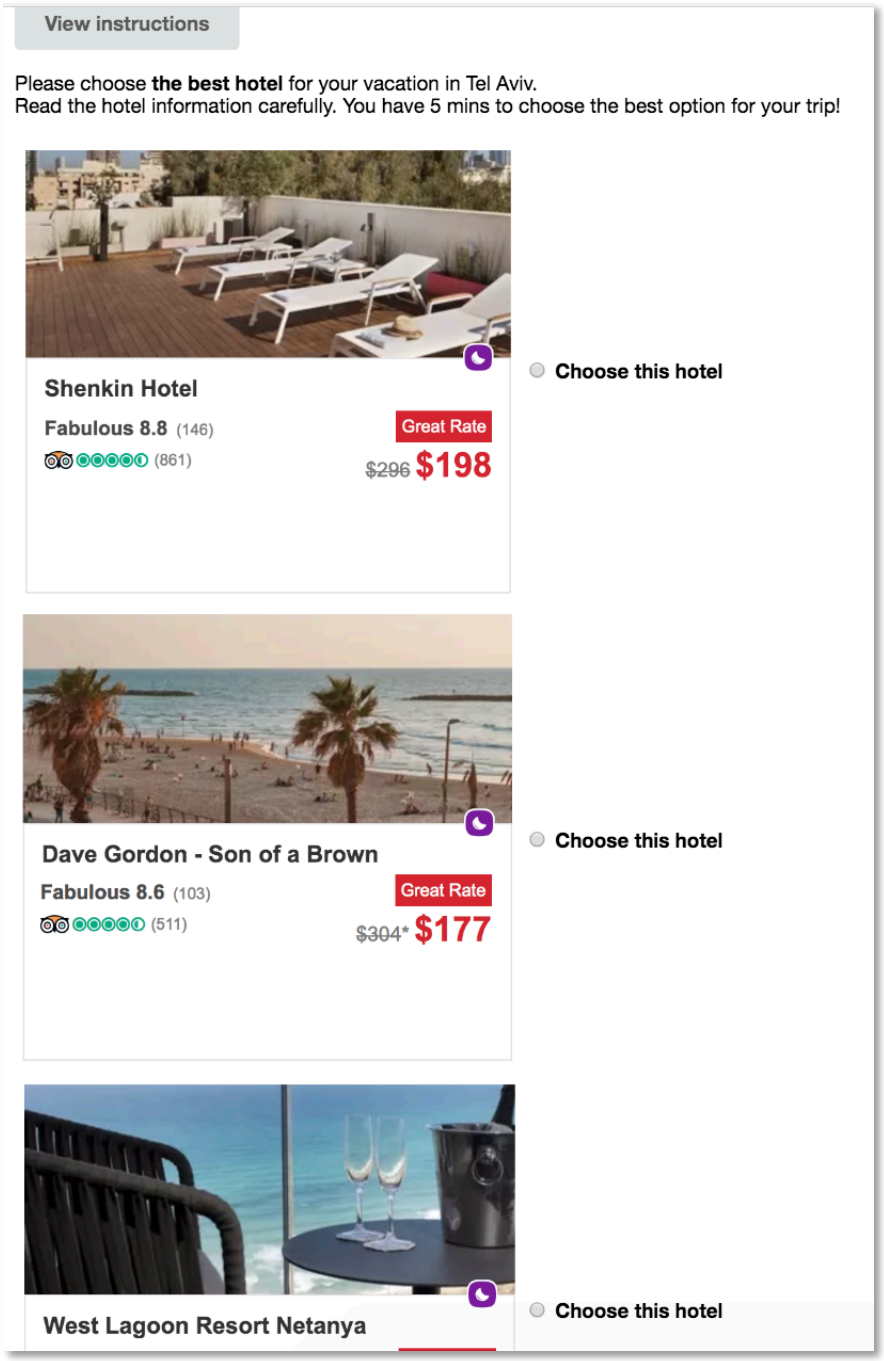


Fig 28. Screenshot of the Experiment for Vertical Layout

Results for Hypothesis H3

(Ert and Fleischer, 2016) study shows that in a vertical layout the preferred positions are the first and the last due to primacy and recency effect. Our results show that in horizontal layout the preferred positions are the first ones. Based on this, H3 should be true. However, we need to assess the results to validate this. In addition, we don't know if the same hotels are preferred based on their attributes (outside their positions).

	Positions:									
Hotels:	1	2	3	4	5	6	7	8	9	10
A	4	7	4	6	3	7	5	2	3	4
B	5	4	11	5	6	6	6	6	6	4
C	20	18	23	23	11	15	14	19	22	15
D	6	7	4	12	6	6	4	4	5	3
E	1	3	8	3	2	3	0	3	3	3
F	5	5	10	4	8	1	6	2	9	9
G	9	3	4	5	5	7	4	2	5	4
H	11	16	6	13	18	18	14	10	16	20
I	11	15	8	8	11	8	10	16	9	10
J	31	32	22	28	25	30	24	27	37	31

Fig 29. Vertical Layout: Hotel Choices in each of the Experimental Condition

A quick analysis showed that the same hotels are **preferred**, C, H and J, as in horizontal layout. However, we will use the same mathematical tool to identify the hotel position preferences.

Below are the results of running the code from Appendix E for Vertical Layout responses:

Hotels Preference	A	B	C	D	E	F	G	H	J
Horizontal	4.44	5.69	**17.81**	5.65	2.83	5.79	4.74	**14.08**	10.4

Positions Preference	A	B	C	D	E	F	G	H	J
Horizontal	10.4	11	8.79	10.33	8.96	10.04	8.55	9.44	12.04

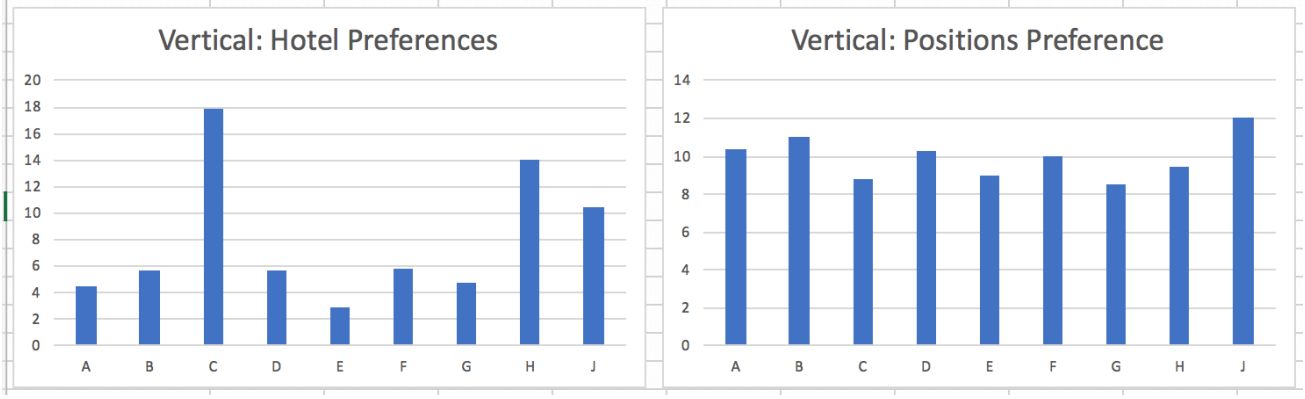


Fig 30. Preferred Hotels and Positions in Vertical Layout

The results show that the preferred hotels are the same (C, H, J) as the horizontal layout (Fig 31).

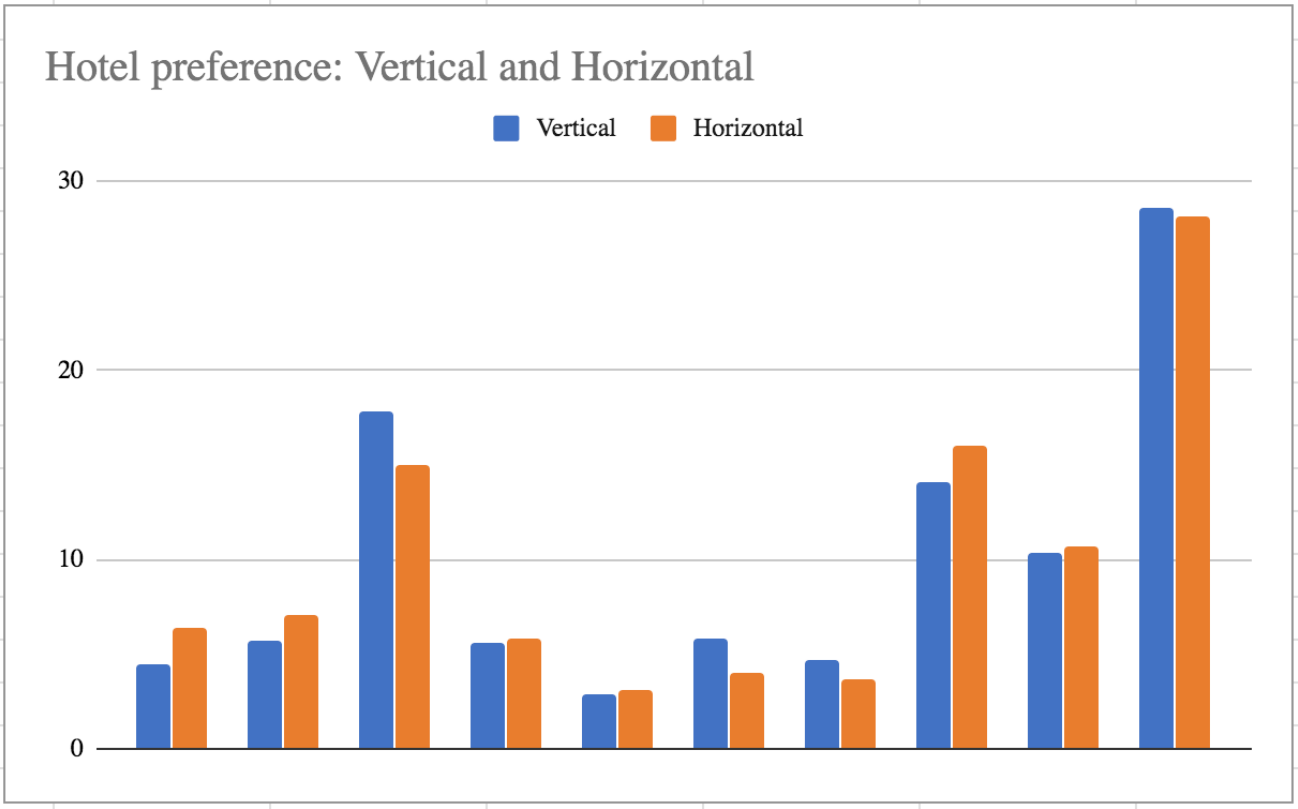


Fig 31. Hotel Preference Comparison

However, we also see that there is a difference in position preference (Fig 31). In vertical layout the second and the last positions are preferred. Hence, it does match the (Ert and Fleischer, 2016) findings. In addition, it is different than the horizontal layout.

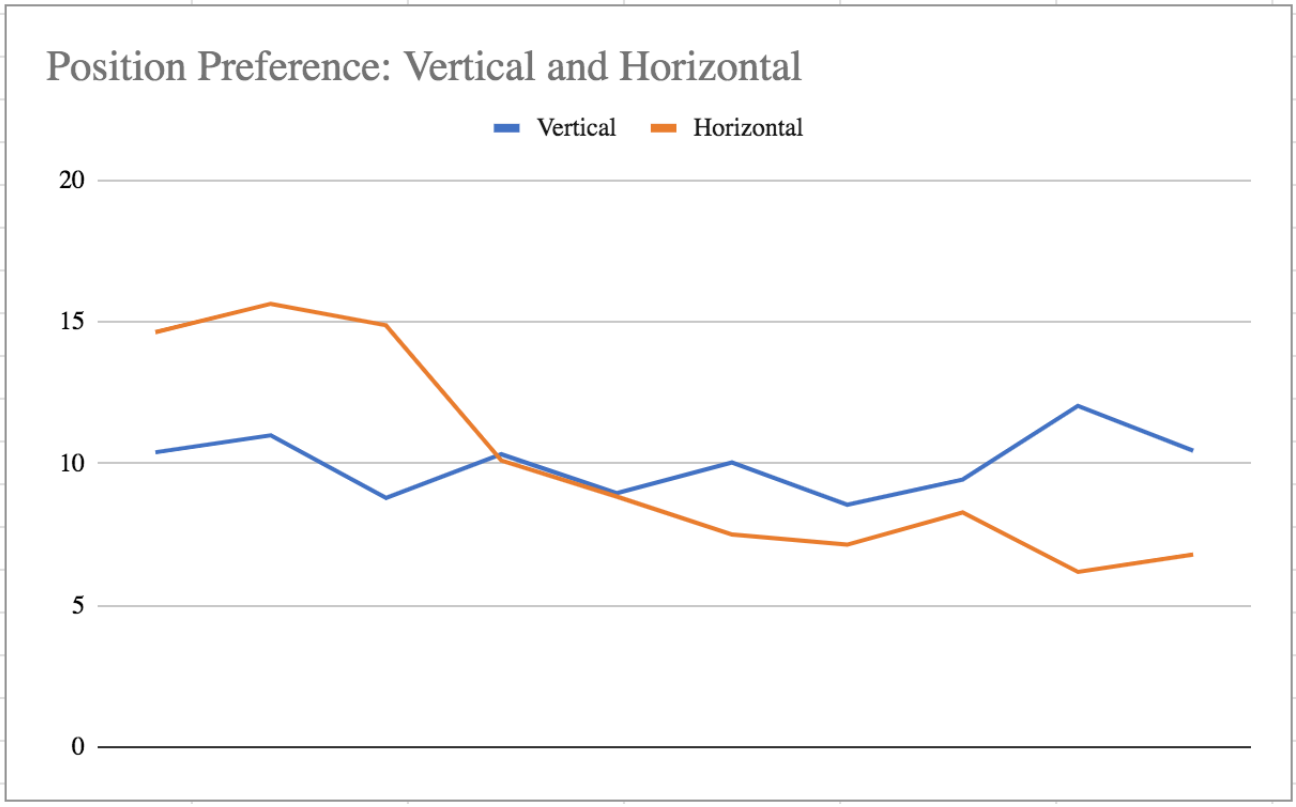


Fig 32. Position Preference Comparison

In conclusion, **hypothesis H3 is accepted** as there is a difference in the likelihood of hotel being chosen between horizontal layout and vertical one based on hotels' position.

Discussion and Applications for Hypothesis H3

Applications

We've observed that more OTAs are experimenting in displaying hotels in horizontal layouts (see Fig 33 and Fig 34)

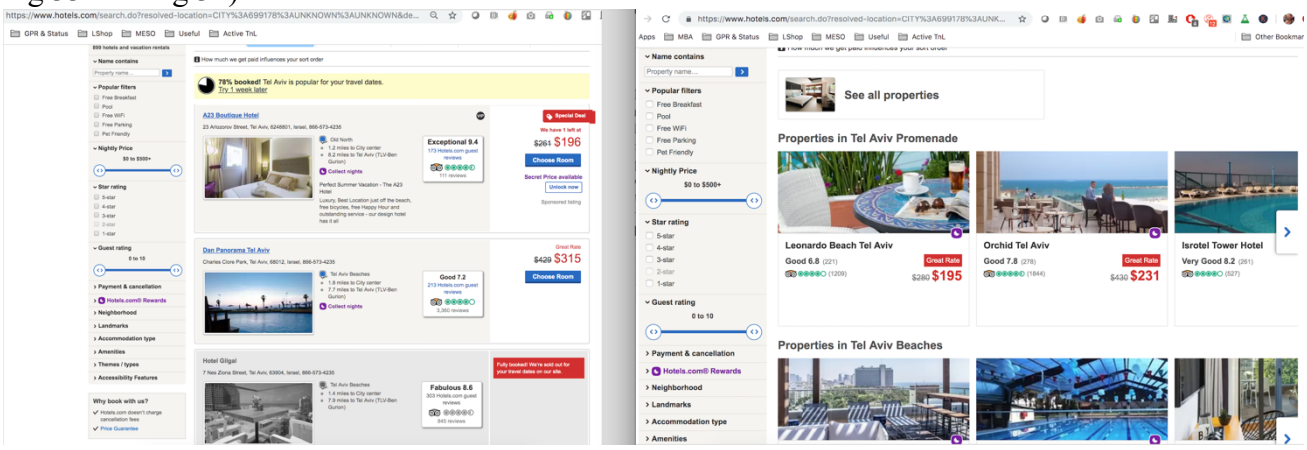


Fig 33. Hotels.com Vertical Layout (right) vs. Horizontal Layout (left)

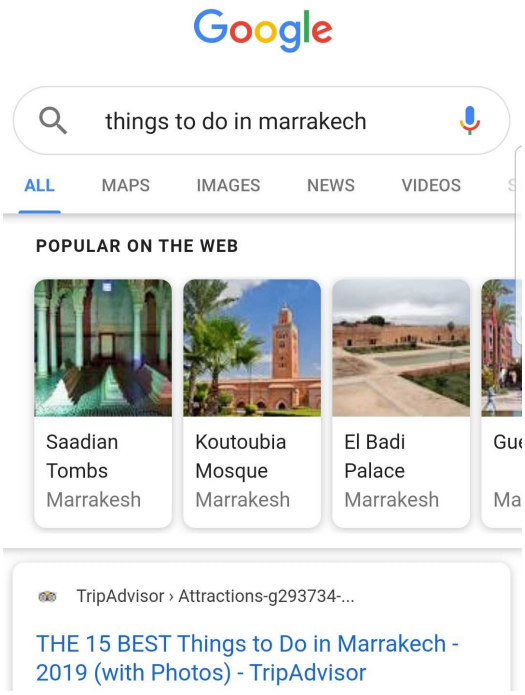


Fig 34. Google Horizontal Layout for Selecting Things to Do.

In this shift, the main implication for OTAs is the awareness of how consumer selection behavior changes from vertical to horizontal presentation. Marketing managers should be aware of the most effective positions for promotions.
As an example, on Expedia.com site sponsored hotels are displayed in specific positions in the list (such as position 1 and 7). In addition, other messages appear in specific position (such as a fear of loss message on position 7 on Expedia). (see Fig 35)

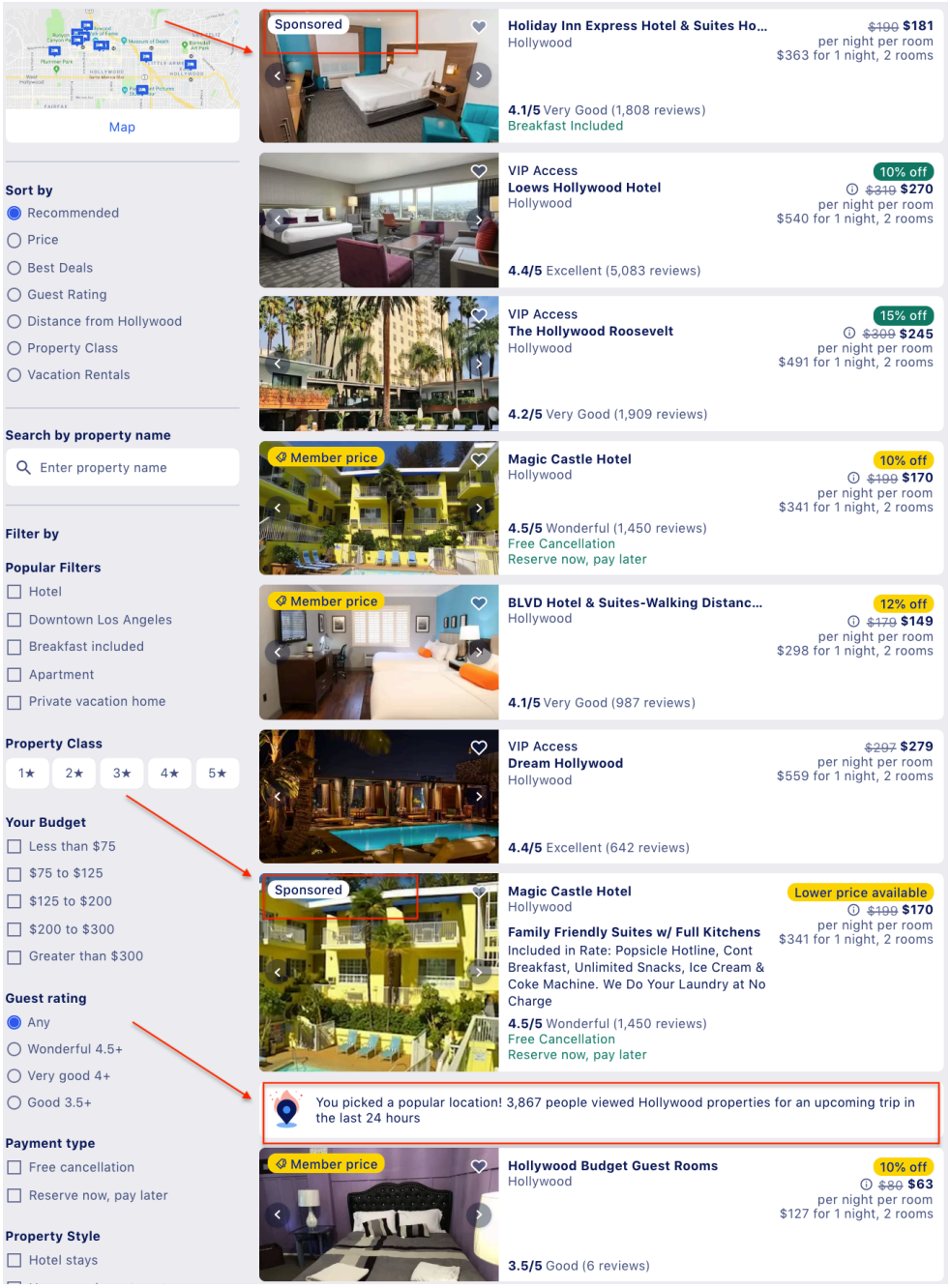


Fig 35. Expedia.com Example of Positioning

If Expedia would move to a horizontal layout, understanding the shift in position preferences is key in order to maintain or even improve their revenue from the sponsored hotels.

Project Limitation

Choice Number

This study demonstrates the evaluation and choice criteria from the consideration set to the choice set to the ultimate hotel selection (Fig 36).

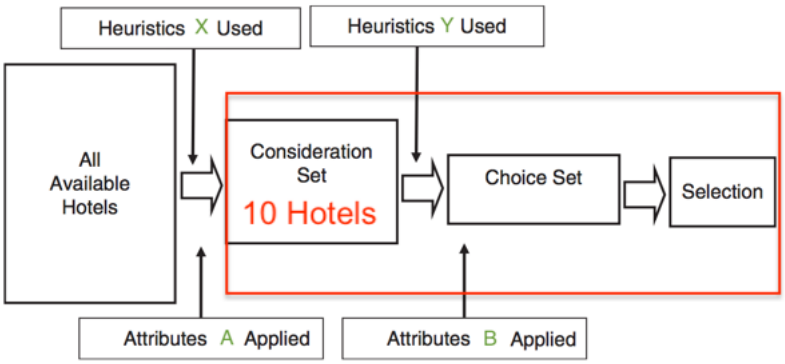


Fig 36. Stage of Assessment for this Study

However, this study doesn't address the choice and evaluation criteria from All Available Hotels to a Consideration Set. If we run the same experiment with higher number of hotels, the results might differ. Park and Jang (2013) demonstrated that having more than 22 choices increased the likelihood of making 'no choice' or having regret after making a choice. It is worth testing with more hotel choices and assess the following:

- Does position have the same impact when product assortment is larger?
- Does elimination by aspects work the same way for a higher number of hotels? (e.g. is the list of preferred hotels similar in a larger choice set (22) vs. smaller (10)?)

Proximity & Context Effect

This study doesn't assess if proximity to focal items has a strong effect on an item's choice probability when the product assortment is larger.

As seen from (Kim J et all, 2018) study, there is a context effect (decoy or compromise effect) when selecting hotels. This paper doesn't assess whether hotels next to each other influenced the choice by introducing a context effect (besides the positioning effect).

Scroll Depth

The scroll depth was not measured in this study. It would have been interesting to track users and see how far on the right they scroll in a horizontal setup. One of the assumptions is that people might not go all the way to the end of the list in a horizontal layout compare to a vertical one.

Sort by…

This study is not looking if hotels are sorted by a specific attribute due to the fact that the test is not done on a real OTA site. Hence, the customers don't have access to filters and sort by functionalities that they would normally have. For example, if a customer decides to sort by the list of hotels based

on price, would they scroll all the way down in a vertical list and pick the most expensive one? This study doesn't address the preference for specific positions in an ordered list (by price, by ratings, by stars etc.)

Hotels Selection Market

One of the possible limitations is the fact that the results might not be generalizable to all hotels or all markets. The hotel selection in the experiment feature beach vacation in Tel Aviv. Same experiment can be applied to other type of market to see if the same results will occur.

Future studies should seek to verify all these limitations to further clarify their boundaries.

Conclusion & Recommendations

This paper has a number of conclusions which are an addition to tourism decision-making literature. First, it provides evidence that hotel selection is influenced by evaluation criteria (a heuristic) and choice criteria (selection or rejection based on attributes).
Second, the evaluation criteria in a horizontal layout is influenced by positioning effect when choosing from non-identical items and a high involvement decision is performed. T**he first positions** are most likely to be chosen in a horizontal layout compare to **first and last ones** in a vertical layout.

This study makes a valuable contribution towards understanding how people chose a hotel in different UI (user interface) layouts and how heuristics around positioning play an important role in the evaluation criteria when a high involvement decision is at stake. This is very important findings for OTAs while they are experimenting different layouts and presentation to the customers. While at face value it seems harmless, it might impact the customer behavior in undesirable ways that might result in revenue losses. The main implication for OTAs is the awareness of how consumer selection behavior changes from vertical to horizontal presentation. Marketing managers should be aware of the most effective positions for promotions.

Some recommendations for OTAs will be to:

1. Promote sponsored products (aka hotels) at top positions in a horizontal layout and top & bottom positions in a vertical one. This will make people select those products more, thus, increasing OTAs' revenue from the sponsors.
2. Help users discover specific products by showcasing them at specific position on their own sites or other sites. If the OTAs are present on meta sites that aggregate hotels from multiple OTAs (such as meta sites: TripAdvisor.com, Kayak.com, Trivago.com), they should negotiate to have their products showcasing on the same positions mentioned at #1. This will increase their revenue knowing that people will select those positions.
3. Predict the impact (such as monetary) if they change their layout. Hence, if they decide to switch from showcasing their products vertically to a horizontal view, then OTAs should move all the products previously in the bottom to the beginning of the list in a horizontal layout. This will assure that there won't be any revenue loss or any share of bookings shifting to other hotels.

In addition, the analysis technique used, can be leverage on future studies or even in past studies in order to be able to separate different preferences that might influence a final decision. This study shows how can non-negative matrix factorization technique can be used for any other study to decompose different types of entities that interact in order to make a final outcome. For example, this technique can be applied to the other studies to separate the preferences for a product attribute vs. heuristics (such as framing, positioning, decoy effect, loss aversion etc.).

Appendix

Appendix A: Compensatory vs. Non-Compensatory Decision Making

"Compensatory decision-making strategies are rational decision choices that are represented by multi-attribute utility models (Keeney and Raiffa 1976; Zeleney 1976). Compensatory decision making involves identifying a set of attributes applicable to the decision, assigning a relative importance or weight to each attribute, computing an overall score for each option based on the attribute weight, and selecting the option with the best score. Compensatory decision making is based on utility maximization since the option(s) with the highest sum of the weighted utilities are selected. In compensatory decisions, a negative value on one attribute can be compensated by an equal or higher value on another attribute. For example, high rent (negative attribute) for one apartment may be compensated by the better location (positive attribute) of that apartment.

In contrast, **non-compensatory decision rules** are those that shortcut or simplify the compensatory process by applying heuristics to quickly evaluate the alternatives with minimal effort. Non-compensatory decision rules can allow faster decisions with acceptable losses of accuracy. They are represented by decision strategies such as the "Elimination by Aspect" strategy (Tversky 1972) and the lexicographic rule (Svenson 1979). For example, in a non-compensatory strategy, a high rent for one apartment eliminates that option from the consideration set, with the better location unable to compensate for the negative high-rent attribute. " (Lee and Anderson 2009)

Appendix B: Experiment Condition

Detailed Instructions
You are traveling for leisure to Tel Aviv for one week with another adult (friend, family member or significant other etc.)
1. Choose by clicking "Choose this hotel".
Please read carefully the information about each hotel provided You have 5 minutes to choose the best option for your trip! Select the hotel by clicking the radio button below the hotel.

Instruction on the page

Please choose **the best hotel** for your vacation in Tel Aviv.
Read the hotel information carefully. You have 5 mins to choose the best option for your trip!

Hotel List

The Seasons on the Sea

Good 7.0 (41)

(461)

Great Rate

~~$456~~ **$174**

Choose this hotel

Hotel De La Mer – by Townhotels

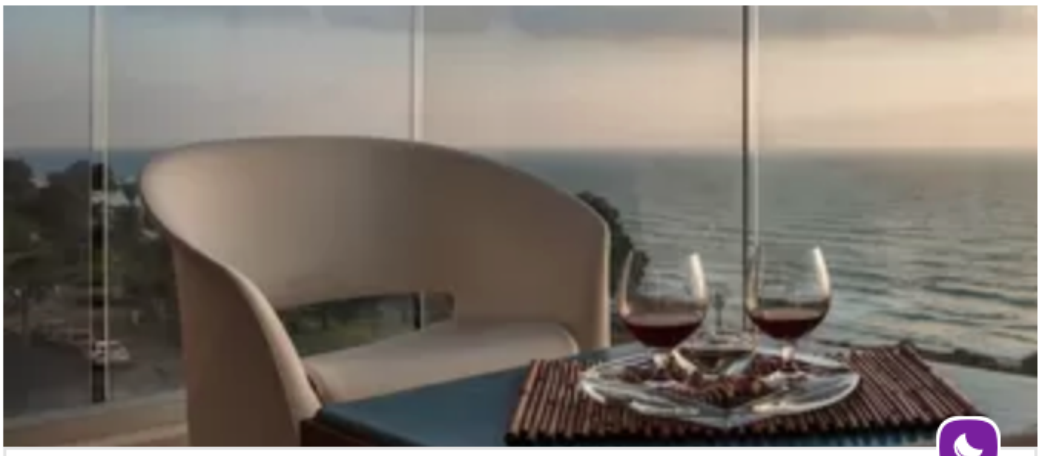
Very Good 8.2 (263)

(523)

Great Rate

~~$358~~ **$175**

Choose this hotel



Azimut Hotel Medi Terre Netanya

Superb 9.0 (83)

(49)

Great Rate

~~$346~~ **$184**

Choose this hotel

Hotel Indigo Tel Aviv - Diamond District

Very Good 8.0 (83)

(437)

Great Rate

~~$600~~ **$168**

Choose this hotel

Shenkin Hotel

Fabulous 8.8 (146)

(861)

Great Rate

~~$296~~ **$198**

Choose this hotel

Dave Gordon - Son of a Brown

Fabulous 8.6 (103)

(511)

Great Rate

~~$304*~~ **$177**

Choose this hotel

Leonardo Plaza Netanya

Very Good 8.2 (74)

(559)

Great Rate

~~$270~~ **$195**

Choose this hotel

West Lagoon Resort Netanya

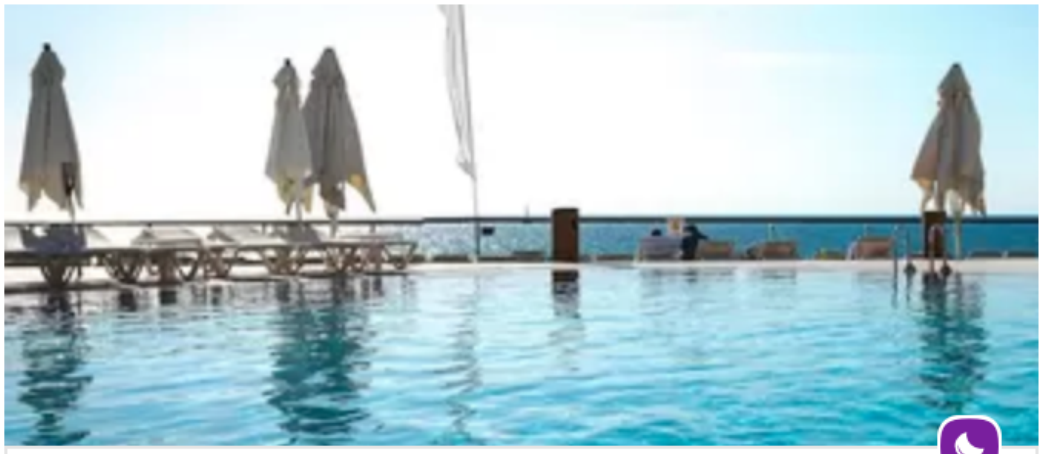
Fabulous 8.6 (168)

(405)

Great Rate

~~$609~~ **$195**

Choose this hotel



Daniel Hotel Herzliya

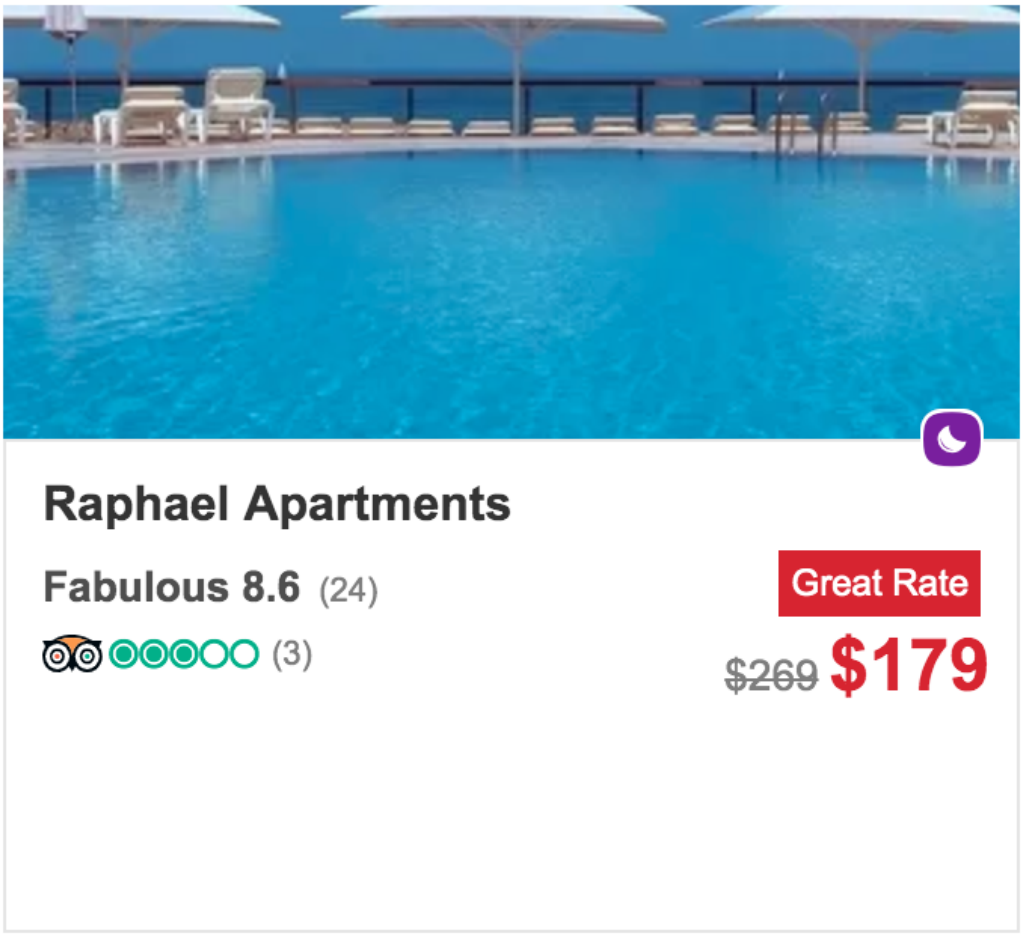
Good 7.4 (139)

(1543)

Great Rate

~~$377~~ **$195**

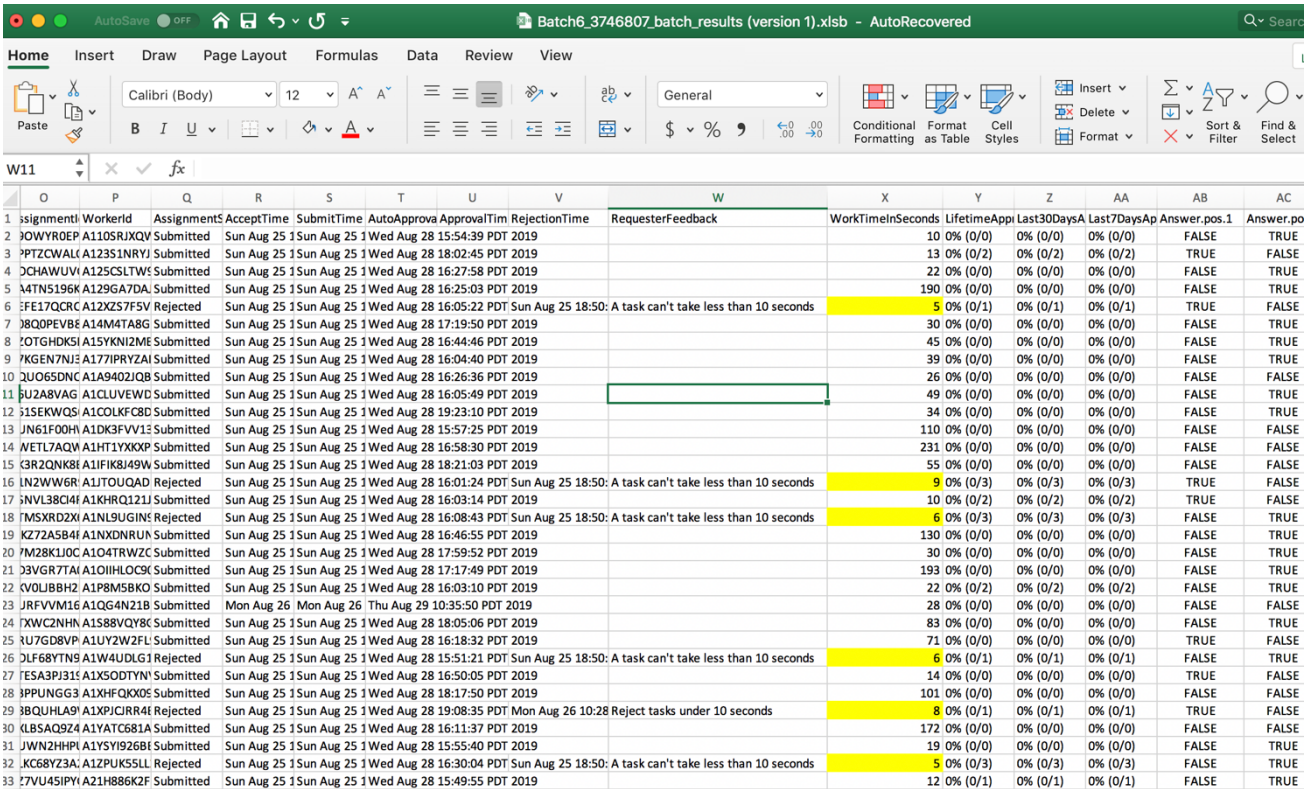
Choose this hotel



Choose this hotel

Appendix C: Invalid Answers

Answers that took less that 10 seconds were rejected.



	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC
1	ssignmentI	WorkerId	AssignmentS	AcceptTime	SubmitTime	AutoApprova	ApprovalTim	RejectionTime	RequesterFeedback	WorkTimeInSeconds	LifetimeAppi	Last30DaysA	Last7DaysAp	Answer.pos.1	Answer.po
2	)OWYR0EP	A110SRJXQV	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	15:54:39 PDT	2019		10	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
3	)PTZCWALI	A123S1NRYJ	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	18:02:45 PDT	2019		13	0% (0/2)	0% (0/2)	0% (0/2)	TRUE	FALSE
4	)CHAWUVI	A125CSLTW9	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:27:58 PDT	2019		22	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
5	44TN5196K	A129GA7DA	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:25:03 PDT	2019		190	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
6	:FE17QCRC	A12XZS7F5V	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:05:22 PDT	Sun Aug 25 18:50:	A task can't take less than 10 seconds	5	0% (0/1)	0% (0/1)	0% (0/1)	TRUE	FALSE
7	)8QOPEVBE	A14M4TA8G	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	17:19:50 PDT	2019		30	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
8	:OTGHDK5I	A15YKNI2ME	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:44:46 PDT	2019		45	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
9	7KGEN7NJ3	A177IPRYZAI	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:04:40 PDT	2019		39	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
10	QUO65DNC	A1A9402JQB	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:26:36 PDT	2019		26	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
11	5U2A8VAG	A1CLUVEWD	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:05:49 PDT	2019		49	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
12	51SEKWQS	A1COLKFC8D	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	19:23:10 PDT	2019		34	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
13	JN61F00H	A1DK3FVV1S	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	15:57:25 PDT	2019		110	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
14	/ETL7AQW	A1HT1YXKXP	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:58:30 PDT	2019		231	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
15	3R2QNK8E	A1IFIK8J49W	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	18:21:03 PDT	2019		55	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
16	LN2WW6R	A1JTOUQAD	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:01:24 PDT	Sun Aug 25 18:50:	A task can't take less than 10 seconds	9	0% (0/3)	0% (0/3)	0% (0/3)	TRUE	FALSE
17	5NVL38CI4I	A1KHRQ121J	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:03:14 PDT	2019		10	0% (0/2)	0% (0/2)	0% (0/2)	TRUE	FALSE
18	7MSXRD2XI	A1NL9UGIN9	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:08:43 PDT	Sun Aug 25 18:50:	A task can't take less than 10 seconds	6	0% (0/3)	0% (0/3)	0% (0/3)	FALSE	TRUE
19	KZ72A5B4I	A1NXDNRUN	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:46:55 PDT	2019		130	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
20	7M28K1J0C	A1O4TRWZC	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	17:59:52 PDT	2019		30	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
21	03VGR7TA	A1OIIHLOC9(	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	17:17:49 PDT	2019		193	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
22	KV0LJBBH2	A1P8M5BKO	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:03:10 PDT	2019		22	0% (0/2)	0% (0/2)	0% (0/2)	FALSE	TRUE
23	JRFVVM16	A1QG4N21B	Submitted	Mon Aug 26	Mon Aug 26	Thu Aug 29	10:35:50 PDT	2019		28	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
24	TXWC2NHN	A1S88VQY8(	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	18:05:06 PDT	2019		83	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
25	RU7GD8VP	A1UY2W2FL	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:18:32 PDT	2019		71	0% (0/0)	0% (0/0)	0% (0/0)	TRUE	FALSE
26	DLF68YTN9	A1W4UDLG1	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	15:51:21 PDT	Sun Aug 25 18:50:	A task can't take less than 10 seconds	6	0% (0/1)	0% (0/1)	0% (0/1)	FALSE	TRUE
27	TESA3PJ31S	A1X5ODTYN'	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:50:05 PDT	2019		14	0% (0/0)	0% (0/0)	0% (0/0)	TRUE	FALSE
28	3PPUNGG3	A1XHFQKX0S	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	18:17:50 PDT	2019		101	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
29	3BQUHLA9'	A1XPJCJRR4(	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	19:08:35 PDT	Mon Aug 26 10:28	Reject tasks under 10 seconds	8	0% (0/1)	0% (0/1)	0% (0/1)	TRUE	FALSE
30	KLBSAQ9Z4	A1YATC681A	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:11:37 PDT	2019		172	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	FALSE
31	JWN2HHPI	A1YSYI926B(	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	15:55:40 PDT	2019		19	0% (0/0)	0% (0/0)	0% (0/0)	FALSE	TRUE
32	KC68YZ3A(	A1ZPUK55LL	Rejected	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	16:30:04 PDT	Sun Aug 25 18:50:	A task can't take less than 10 seconds	5	0% (0/3)	0% (0/3)	0% (0/3)	FALSE	TRUE
33	7VU45IPY(	A21H886K2F	Submitted	Sun Aug 25 1	Sun Aug 25 1	Wed Aug 28	15:49:55 PDT	2019		12	0% (0/1)	0% (0/1)	0% (0/1)	FALSE	TRUE

Appendix D

Python Code for Non-negative Matrix Factorization of the Horizontal Results.

```
import numpy as np
from sklearn.decomposition import NMF

R = np.array([[7, 12, 16, 5, 7, 4, 1, 1, 9, 3],
[16, 12, 16, 3, 4, 2, 4, 0, 4, 7],
[21, 24, 25, 14, 21, 13, 12, 10, 8, 13],
[12, 12, 7, 5, 4, 1, 3, 7, 4, 4],
[5, 7, 6, 2, 4, 2, 1, 1, 2, 1],
[3, 12, 8, 3, 3, 3, 3, 2, 1, 0],
[7, 5, 10, 3, 3, 0, 3, 2, 2, 1],
[34, 21, 29, 16, 12, 13, 12, 13, 7, 8],
[30, 15, 14, 10, 11, 9, 5, 4, 4, 5],
[34, 50, 40, 35, 25, 24, 24, 32, 22, 23]])

model = NMF(n_components=1, init='random', random_state=0, max_iter=30000)
P = model.fit_transform(R)
Q = model.components_

print('Model errors')
print(model.reconstruction_err_)
print('Hotel preferences')
print_data(P)
print('Position preferences')
print_data(Q.T)
```

Appendix E

Python Code for Non-negative Matrix Factorization of the Vertical Results.

```
import numpy as np
from sklearn.decomposition import NMF

R = np.array([[4, 7, 4, 6, 3, 7, 5, 2, 3, 4],
[5, 4, 11, 5, 6, 6, 6, 6, 6, 4],
[20, 18, 23, 23, 11, 15, 14, 19, 22, 15],
[6, 7, 4, 12, 6, 6, 4, 4, 5, 3],
[1, 3, 8, 3, 2, 3, 0, 3, 3, 3],
[5, 5, 10, 4, 8, 1, 6, 2, 9, 9],
[9, 3, 4, 5, 5, 7, 4, 2, 5, 4],
[11, 16, 6, 13, 18, 18, 14, 10, 16, 20],
[11, 15, 8, 8, 11, 8, 10, 16, 9, 10],
[31, 32, 22, 28, 25, 30, 24, 27, 37, 31]])

model = NMF(n_components=1, init='random', random_state=0, max_iter=30000)
P = model.fit_transform(R)
Q = model.components_

print('Model errors')
print(model.reconstruction_err_)
print('Hotel preferences')
print_data(P)
print('Position preferences')
print_data(Q.T)
```

Appendix F

There are already online systems that help customers choosing the optimal solution that matches their preferences. “Decision support tools, also known as Recommendation Systems (RSs), have been developed to address these concerns. In the tourism field, they are referred to as Tourism Recommendation Systems (TRSs). Tourists and tourism providers can search, select, compare and make decisions almost instantly, and more efficiently than ever.” (Thiengburanathum, 2018)

“A recommendation engine filters the data using different algorithms and recommends the most relevant items to users. It first captures the past behavior of a customer and based on that, recommends products which the users might be likely to buy.” (Analytics Vidhya, 2019)

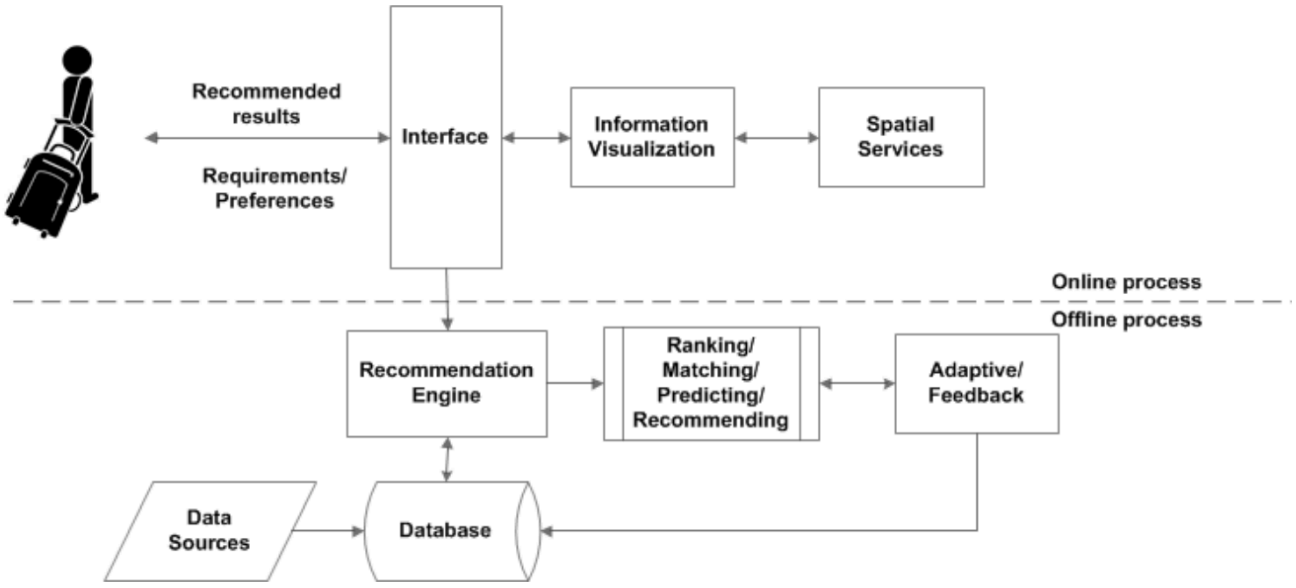


Fig 31. Conventional architecture of TRS. (Thiengburanathum, 2018)

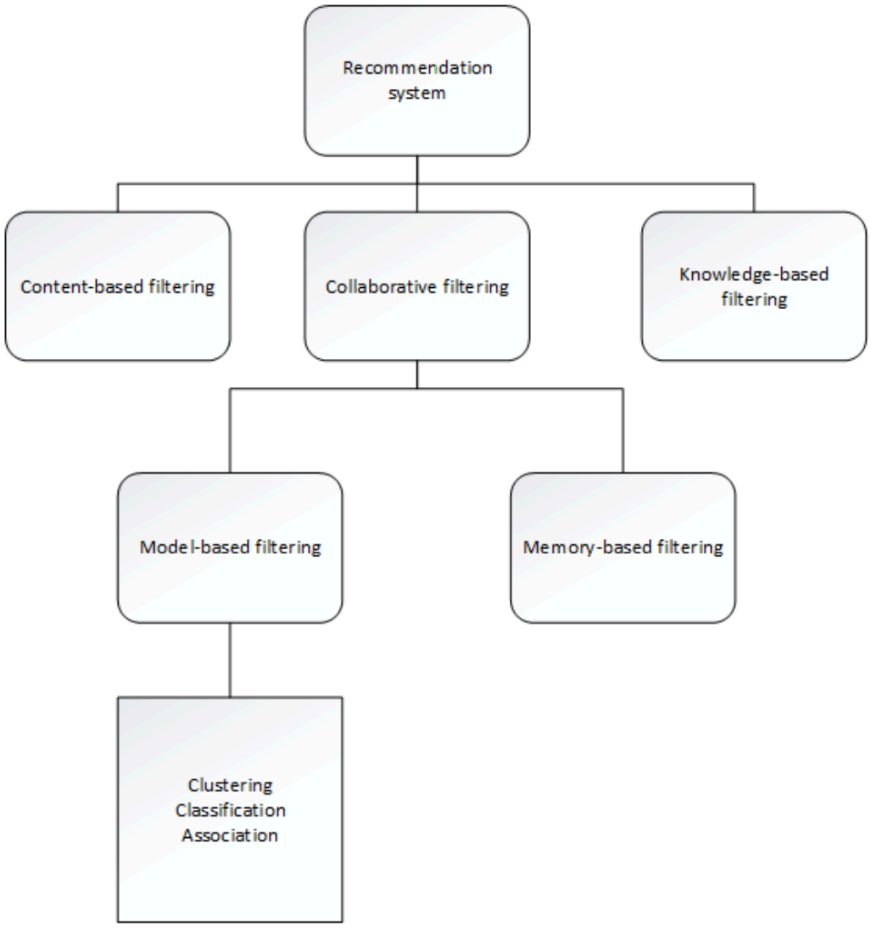


Fig Y. Recommendation Engine Techniques (Thiengburanathum, 2018)

Appendix G

Differences between Positivism and Interpretivism philosophies and their characteristics.

	Quantitative aka Positivism (Deductive : Theory before research)	Qualitative aka Interpretivism (Inductive: Research before theory)
FEATURES	- Use large samples - Hypothesis testing - Produce precise, objective, quantitative data - Results with high reliability, low validity - Results to be generalized from sample to population	- Use small samples - Generating theory - Rich, subjective, qualitative data - Findings with low reliability, high validity - Findings to be generalized from one setting to a similar setting
METHODOLOGIES	- Experimental studies - Surveys (primary & secondary) - Cross-sectional studies (same time, different context) - Longitudinal studies (observing for long period of time)	- Hermeneutics - Ethnography (researcher becomes member of the group being studied) - Participative inquiry - Action research - Case studies - Grounded studies - Feminism, gender, ethnicity studies
Research Questions	- Express a relationship between variables (hypothesis) - Imply the possibility of empirical testing H0 - 2 variables are not dependent; H1 the opposite	- Grand tour question, open-ended, - Start by "what/how" - Avoid " cause/relationship/ association"
Collect Data		Issues: - Valid but not reliable - Contextualized (time, location, legal, social etc.)
Sample	- Random sample to generalize - Minimum sample size(bigger variation, bigger size)	- No need for a random sample (bec it doesn't require generalization) • Snowball sampling • Judgmental/purposive sampling: selected base don experience • Natural/convenience sample (only these employees are avail at this time)
Methods of collecting data	- Interviews - Questionnaires - Critical incident technique (recollection of key facts) -	- Interviews (open ended vs. closed questions) - Critical incident technique (recollection of key facts) - Focus group (selected participants discuss their reaction/feelings on a product/service) 5-10 participants. - Delphi method - Protocol analysis (retrospective & concurrent verbalization) - Diary method (people record action/info over a timeframe) - Observation (collect data in natural settings or laboratory)
Analyzing Data	- Statistic models	- Comprehending - Synthetizing (general explanation) - Theorizing (make links with theory, construct theory from data by induction) - Recontextualizing (generalization ?! I thought you don't in the qualitative approach) - Quantifying (number of a pattern that occurred) **Stages**: 1. Data reduction (reduce, restructure, detextualizing /diagram) 2. Data displays (summarize data in a visual format: network, matrix,) 3. Conclusion & Verification (credibility, transferability/generalization, **Content analysis** - Data transform into numerical data for analysis (coding units & frame) **Discourse analysis** - Analysis of social action/theory, language **Methods where collecting & analyzing are intertwined**: 1. Grounded method (collect, analyze, theorize of data together) 2. Repertory grid technique (matrix with the personal construct of the interviewee) 3. Cognitive mapping (diagram for the #2)

Adapted from (Saunders et al., 2007).

Appendix H

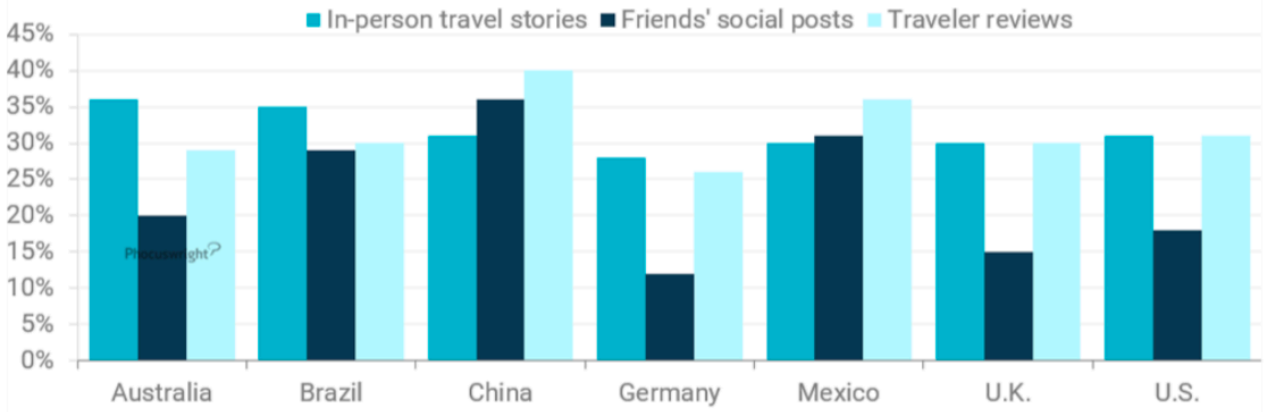
"Amazon Mechanical Turk (MTurk) is a crowdsourcing marketplace that makes it easier for individuals and businesses to outsource their processes and jobs to a distributed workforce who can perform these tasks virtually. This could include anything from conducting simple data validation and research to more subjective tasks like survey participation, content moderation, and more. MTurk enables companies to harness the collective intelligence, skills, and insights from a global

workforce to streamline business processes, augment data collection and analysis, and accelerate machine learning development.
While technology continues to improve, there are still many things that human beings can do much more effectively than computers, such as moderating content, performing data deduplication, or research. Traditionally, tasks like this have been accomplished by hiring a large temporary workforce, which is time consuming, expensive and difficult to scale, or have gone undone. Crowdsourcing is a good way to break down a manual, time-consuming project into smaller, more manageable tasks to be completed by distributed workers over the Internet (also known as 'microtasks')." (MTurk, 2019)

Appendix I

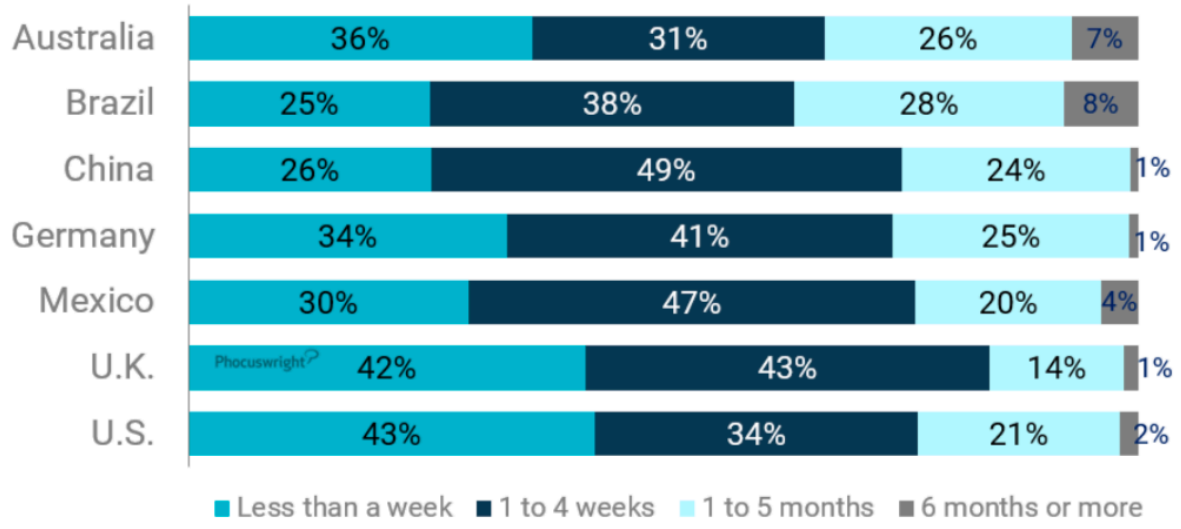
Travel is personal depending on many factors: age, length of trip, number of trips taken, travel party composition, traveler persona (foodie, city explorer, beachgoer etc.), time taken to decide between destinations, trip planning motivations. See the following Phocuswright (2019) survey results:

Figure 11: Trip Planning Motivations, Peer Content, Share (%)



Question: Which of the following have inspired you to seriously consider planning a new trip, or visit a new travel destination? *Please select all that apply.*
Base: Global leisure travelers who selected a destination independently: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Source: *Destination Decision: How Travelers Choose Where to Go*

Figure 8: Time Taken to Decide Between Destinations, Last Trip, Share (%)



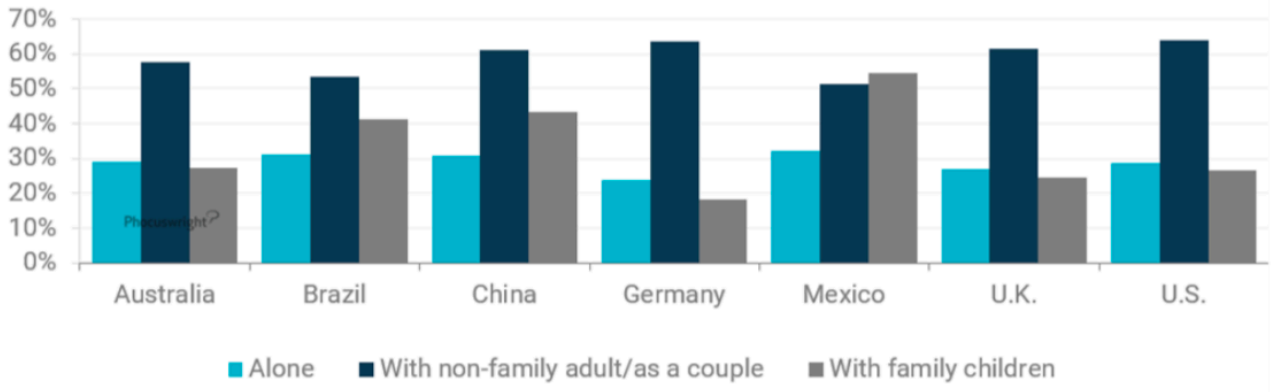
Question: How much time did you spend deciding between destinations for this trip?
Base: Global leisure travelers who decided between destinations: AU (N=127), BR (N=234), CH (N=736), DE (N=188), MX (N=281), U.K. (N=150), U.S. (N=227)
Source: *Destination Decision: How Travelers Choose Where to Go*

Figure 5: Top Ten Traveler Personas, Share (%)

	Australia	Brazil	China	Germany	Mexico	U.K.	U.S.
Avid sightseer	23%	19%	13%	14%	7%	22%	24%
Beachgoer	19%	32%	20%	33%	34%	21%	24%
City explorer	27%	35%	10%	36%	34%	40%	24%
Ecotourist/nature lover	13%	12%	42%	10%	17%	8%	8%
Family holiday maker	22%	24%	27%	19%	32%	23%	25%
Foodie	22%	13%	33%	12%	26%	14%	19%
History buff	15%	14%	12%	14%	12%	13%	16%
Local culture lover	20%	23%	24%	16%	22%	20%	19%
Rejuvenator	23%	11%	20%	41%	13%	16%	21%
Shopper	19%	11%	21%	11%	15%	13%	13%

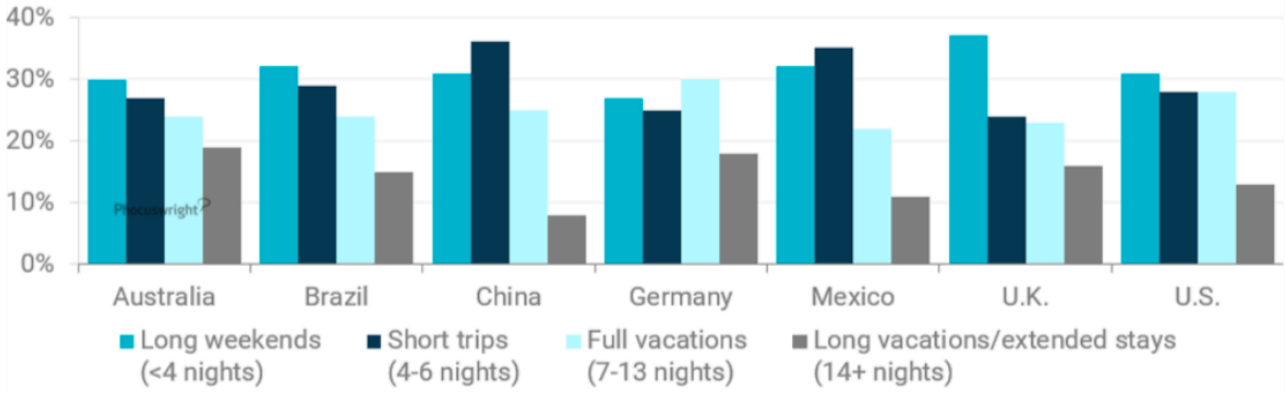
Question: Which of the following best describes you as a traveler? *Please select up to three.*
Base: Global leisure travelers who selected a destination independently: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Note: Top three for respective market highlighted in orange
Source: *Destination Decision: How Travelers Choose Where to Go*

Figure 4: Travel Party Composition for Trips in the Last 12 Months, Share (%)



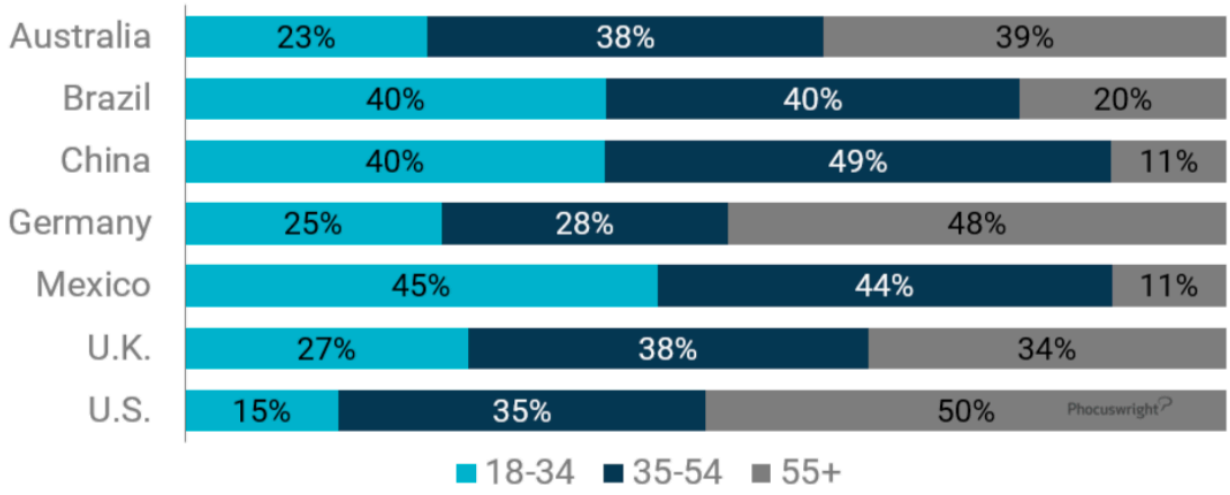
Question: For the leisure trips you took in the past 12 months who did you travel with? *Select all that apply.*
Base: Global leisure travelers who selected a destination independently: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Source: *Destination Decision: How Travelers Choose Where to Go*

Figure 3: Length of Trip, Percentage of Trips Taken



Question: Of the total leisure trips you took in the last 12 months, how many were:
Base: Total trips taken: AU (N=2,708), BR (N=3,568), CH (N=3,361), DE (N=3,123), MX (N=3,732), U.K. (N=3,297), U.S. (N=3,986)
Note: Total trips are based on self-reported number by survey respondents: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Source: *Destination Decision: How Travelers Choose Where to Go*

Figure 2: Traveler Age, Share (%)



Question: Please enter your age.
Base: Global leisure travelers who selected a destination independently: AU (N=865), BR (N=817), CH (N=811), DE (N=862), MX (N=863), U.K. (N=875), U.S. (N=882)
Note: Totals may not add to 100% due to rounding.
Source: *Destination Decision: How Travelers Choose Where to Go*

Appendix J

The main problem in the digital information environment is the information overload, as people have access to more information than ever before. Too much information from too many sources may lead

to information overload due to the cognitive costs associated with information processing (Bettman et al., 1991)

Travelers are often overwhelmed by the huge amount of information online and not able to locate the information they intend to find (Pan and Fesenmaier, 2000). Thus, trip planning on the Web can be a frustrating experience.

Trip planners are looking for all type of information: destination, activities, transportation. (Fig 5)

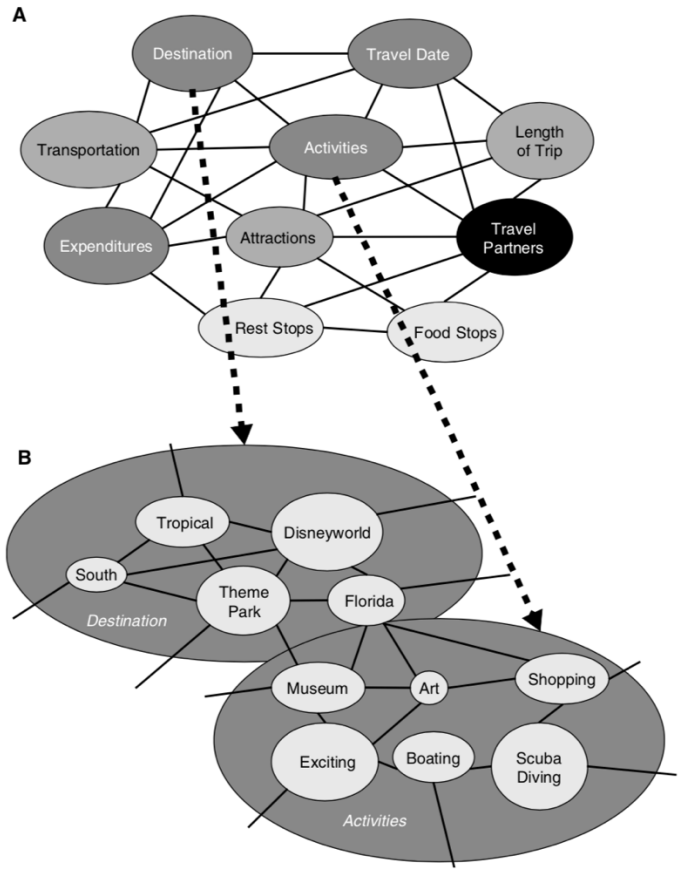


Fig 5. Semantic Mental Model of Travel Planning (Fesenmaier et al., 2006)

OTAs can reduce the window between shopping and booking by offering relevant recommendations from where customers can easily select. This will reduce the friction in the shopping stage of the journey. (Travelport, 2019)

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