POLITECNICO DI MILANO
DEPARTMENT OF MANAGEMENT ENGINEERING

LUXURY AND NECESSITY GOODS:
HOW ANTICIPATED EMOTIONS SHAPE PURCHASE INTENTIONS

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To my supervisor,

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Professors, whose dedication and expertise brought indescribable value. And my colleagues, who made this experience truly remarkable.

To anyone who contributed to my knowledge and development.

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ABSTRACT [English]

In the last decades, the paradigm that consumer decisions are driven only by rational components has been shifted. *Anticipated Emotions (AEs)* - perceived consequences of decision outcome, emerged as valid influencers on behavior. AEs effects can vary depending on what consumers buy, while for peculiar goods may not apply at all. For instance, some scholars assume that frequent purchases of necessity goods might be instinctive and purely rational, while for luxury goods emotional components might be the key decision influencers. AEs effects on necessity vs luxury goods had never been empirically assessed before, therefore this work takes the challenge to evaluate it. Specifically, the study assumes that AEs impact both good categories, however, those effects are significantly different and can be better understood with the valence-based approach: necessity goods are affected more by negative AEs, while luxury goods by positive ones. For reaching the research objective, the conceptual model was developed with the core idea that AEs influences attitudes, which together with subjective norms form the behavioral intention. Relationships within the model were tested by assigning measures to each construct and evaluating them through the self-reported emotions technique. Responses from 203 individuals were evaluated through the PLS-SEM methodology. Results confirmed that (i) both necessity and luxury goods purchase intentions are impacted by AEs, however (ii) the good category necessity vs luxury is a valid moderator, and differences between AEs effects are significant. In particular, (iii) luxury goods are affected by positive AEs, but not negative ones, while (iv) for necessity goods there is a significant influence of negative AEs, but no strong effects of positive ones. Implications of findings both for academics and managers were discussed and reported.

Keywords: Anticipated emotions, Luxury and Necessity goods, PLS-SEM, Consumer Behavior

ABSTRACT [Italian]

Negli ultimi decenni, il paradigma secondo cui le decisioni dei consumatori sono guidate solo da componenti razionali è cambiato. Le emozioni anticipate (AE) - conseguenze percepite dell'esito della decisione, sono emerse come validi fattori di influenza sul comportamento. Gli effetti delle AE possono variare a seconda di ciò che i consumatori acquistano, mentre per beni particolari potrebbero non applicarsi affatto. Ad esempio, alcuni studiosi ipotizzano che gli acquisti frequenti di beni di prima necessità possano essere istintivi e puramente razionali, mentre per i beni di lusso le componenti emotive a chiave delle decisioni potrebbero essere gli influencer. Gli effetti delle AE sui beni di prima necessità rispetto ai beni di lusso non erano mai stati considerati empiricamente prima, per cui questo lavoro ha accettato la sfida di valutarli.Nello specifico, lo studio presuppone che le AE abbiano un impatto su entrambe le categorie di beni, tuttavia, tali effetti sono significativamente diversi e possono essere meglio compresi con l'approccio basato sulla valenza: i beni di necessità sono influenzati maggiormente dalle AE negative, mentre i beni di lusso da quelle positive. Per raggiungere l'obiettivo della ricerca, il modello concettuale è stato sviluppato con l'idea centrale che le AE influenzino gli atteggiamenti, che insieme alle norme soggettive formano l'intenzione comportamentale. Le relazioni all'interno del modello sono state testate assegnando delle misure a ciascun costrutto e valutate attraverso la tecnica delle emozioni auto-segnalate. Le risposte di 203 candidati sono state esaminate attraverso la metodologia PLS-SEM. I risultati hanno confermato che (i) le intenzioni di acquisto di beni di prima necessità e di lusso sono influenzate dalle AE, tuttavia (ii) la categoria dei beni di prima necessità Vs quelli di lusso è un valido moderatore e le differenze tra gli effetti delle AE sono significative. In particolare, (iii) i beni di lusso risentono di AE positive, ma non negative, mentre (iv) per i beni di prima necessità vi è un'influenza significativa di AE negative, ma nessun evidente effetto di quelle positive. Sono state discusse e riportate le implicazioni dei risultati sia per i candidati accademici che per i manager.

Parole chiave: emozioni anticipate, beni di lusso e di necessità, PLS-SEM, comportamento del consumatore

ABBREVIATIONS

AE – Anticipated Emotions

PAE - Positive Anticipated Emotions

NAE - Negative Anticipated Emotions

TPB - Theory o Planned Behavior

TRA – Theory of Reasoned Action

SN – Subjective Norms

MGB – Model of Goal-Directed Behavior

ATF - Appraisal-Tendency Framework

PLS – Partial Least Square

SEM - Structural Equation Modeling

MGA – Multi-Group Analysis

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Chapter 1.

1. INTRODUCTION

1.1. Research motivation and objectives

Every business aims to effectively communicate the value that they offer in order to make more people decide on purchasing their product and/or service, therefore generate revenue for the firm. All marketing managers, have to face the challenge of going deeper in understanding how consumers make their decisions**.** Why they prefer one option to the other one? How much time do they need to decide? What exact rational and emotional components consumers may take into consideration?

Conceptual models were built not only to spot and analyze components that drive behavior but also to be able to predict the behavioral outcomes and to influence them through these components. One of these components that emerged in the last two decades is *Anticipated Emotions (AE)* - perceived consequences of decision outcome.

For example, one can find a great offer for a product: an extraordinary discount due to temporary promotion (e.g., for a new laptop or TV). Many consumers want to take advantage and save money, thinking that this decision will make them feel good, satisfied, and proud that they catch such a great deal. In this case, not purchasing the product now will make them unhappy later. On the other side, maybe a better offer will appear later, and they would regret buying it with a higher price now. Sometimes, the purchased item can turn out to be worse in quality or useless for the consumer: can simply not meet their expectations at all, which will also lead to negative feelings. This case demonstrates anticipated emotional effects in practice.

For the business, AE influences might be extremely relevant, since not wanting to experience negative emotions in the future, consumers may reject even the most extraordinary offers. Marketing managers should consider these effects for a more effective design of marketing offers and communications. This study is aiming to provide comprehensive insights for both academics and practitioners from empirical research.

Starting with the simple consideration that our decisions usually have the ultimate goal to bring us happiness and avoid unhappiness, anticipated emotions are serving as simple and very informative clues in decision-making. For simplicity, Anticipated emotions can be seen as the answer to the question: “How would you feel when the decision for alternative X leads to consequence Y?”

Nowadays due to the great effort of researchers worldwide, we have a better understanding of emotional effects on decision making. However, it has not always used to be this way. It was commonly accepted to think that most rational components drive purchase decisions: individuals will consider price, performance characteristics, etc. Meta-analysis of the field by Jennifer S. Lerner and colleagues reported that attention to the emotional effects started to grow only in the 21st Century (Lerner et al., 2015a). From this moment on, particular attention was also drawn from psychologists and many scientists who concluded that emotions are the dominant driver for the majority of meaningful life decisions (e.g., Ekman 2007, Frijda 1988, Gilbert 2006, Keltner & Lerner 2010, Keltner et al 2014, Lazarus 1991, Loewenstein et al 2001, Scherer & Ekman 1984).

Economics and marketing fields started rapidly diffusing and testing these discoveries from psychologists. For instance, Lerner with colleagues in 2013 conducted experiments to test whether sadness would increase impatience regarding financial decisions. (Lerner JS, 2013) Another study showed that the stock market performance was getting worse when during the World Cup a country’s national soccer team was eliminated (Edmans et al., 2007). This way, with the presence of emotional components, many use cases which seemed unlogical at first, started to become clear. However, almost every new study on this topic highlights the need for additional research and raises further questions.

Researchers went even further and started to distinguish emotions by valence and later by appraisal. The valence-based approach states that emotions can be divided into positive and negative. Moreover, it is assumed that emotions of the same valence would have similar effects. This way people that generally have a good mood and emotions would have more optimistic judgments, while people in bad moods on the contrary are pessimistic (Loewenstein & Lerner, 2003) Since this approach was not sufficient to explain some nonsenses, researchers went beyond valence and presented the Appraisal Tendency Framework (ATF) (Han et al., 2007; Lerner & D Keltner, 2001), which became the first influential multidimensional framework and showed that specific emotions influence our decisions.

While many researchers kept their focus on the *current* feelings to get informative clues for predicting judgments (e.g. the feelings-as-information theory by Schwarz, 2012), ignoring anticipation of the affective consequence of current decisions, others had shown that emotions that we expect to experience in the future are driving the decision-making process (Barbara A. Mellers & McGraw, 2001). The idea is that when individuals consider purchase decisions, in the end, the key personal input is whether purchasing or non-purchasing will make them feel better.

Anticipated emotions already have proven their relevance in a broad variety of contexts, such as preventing environmental risks (Böhm & Pfister, 2008), violating automobile driving rules (Parker, West, Stradling, & Manstead, 1995), gambling (Mellers, Schwartz, & Ritov, 1999), adopting sexual precautions to protect one from contracting STDs (Richard, Van der Pligt, & de Vries, 1995) and others.

Even if many researchers in the last two decades tested the effect of anticipated consequences on behavioral intentions (Barbara A. Mellers & McGraw, 2001; Patrick et al., 2009; Rivis et al., 2009), several others highlighted their importance and a strong need for additional research (Bettiga et al., 2020a; Perugini & Bagozzi, 2001a; Rivis et al., 2009; Taylor et al., 2016).

Despite the increasing effort of researchers to understand the role of anticipated emotions, some studies have reported medium-large correlations between anticipated emotions and intentions (e.g., Richard et al., 1998), other studies have found a weak correlation (e.g., O'Connor & Armitage, 2003), which shows the importance of additional research. This thesis will contribute to the field by providing additional data and observations about the strength of these correlations.

Anticipated emotions were integrated in different ways in the existing behavioral models. One of the most influential frameworks is the Model of Goal-directed Behaviours (Perugini & Bagozzi, 2001b). The authors have introduced a new construct: Desires as a proximal cause of intentions. Moreover, they suggested adding anticipated emotions – perceived consequences of goal achievement and goal failures, as determinants of desires. All other traditional TBP antecedents (subjective norms, attitudes, and perceived behavioral control), according to the new perspectives, should work through desires. (Perugini & Bagozzi, 2001b).

Even if the model was performing rather well, the authors highlighted improvement points. Especially the fact that model components and the relationship between them may depend on, for instance, "personality styles related to confidence, doubt and coping" ((Perugini & Bagozzi, 2001c)(Perugini & Bagozzi, 2001c).

Moreover, the same authors in later studies highlighted that the effect of Anticipated emotions (AE) may not apply for some contexts or good categories at all (Bagozzi et al., 2016). The research work present herein helps to close this knowledge gap. The research work present herein helps to close this knowledge gap.

Some research regarding how the impact of AE depends on purchase item category was done. For example, it was proven that experience-based purchases are affected by anticipated emotions way more than material-based ones (Kumar et al., 2014) One very interesting dimension was never touched by researchers yet: necessity versus luxury goods. The distinction between necessity and luxury goods has proven to be widely used and effective in the managerial field, however, it was never studied in terms of anticipated emotions.

This dimension is very promising and few studies already raised questions in this direction. For instance, Bagozzi and colleagues specifically suggested researchers to pay attention to luxury goods purchases (Bagozzi et al., 2016). Indeed, we might assume that for luxury goods, positive AEs might have a key role in purchase decisions: satisfaction, excitement, and pride are some of the feelings consumers may experience by anticipating having luxury items. It would be very useful for academics and especially practitioners to understand deeper AE's effects on luxury goods.

For necessity goods, the current state of knowledge is specifically interesting. Since Necessity items are defined as something everyone needs, indispensable things and their consumption is essential to human survival or is needed for maintaining a certain standard of living, buyers are taking into account only the price-quality ratio, and the price is usually a defining variable for the purchase decision (Bochanczyk-Kupka, 2019, p. 260) In other words, it is commonly accepted that regarding purchase decisions in case of necessity goods only rational variables (like price) are taken into account and the emotional side is mostly neglected.

Respected scholars in the field of Anticipated Emotions have doubts in regards to necessity goods. Bagozzi assumes that "the frequent purchases might be instinctive and not imply AEs" (Bagozzi et al., 2016). Clearly, there are many unanswered questions in this direction and this thesis work is aiming to provide those answers.

Therefore the research objective of this study is **to examine the impact of consumer's positive and negative anticipated emotions on purchase intentions depending on the good category (necessity vs luxury).** More specifically, clarify whether AEs apply to necessity goods and whether they apply for luxury goods. If they do, through what mechanism do AEs apply exactly, and what types of AEs are more and/or less relevant for predicting purchase behaviors.

Answering these research questions will allow closing one of the existing knowledge gaps in the field of anticipated affects and consumer behavior in general. Moreover, having a better understanding of what is the role of AEs regarding purchase decisions towards luxury and necessity goods would get much better insights to the managers and help them influence the desired behavior.

1.2. Structure of the manuscript

The manuscript includes 7 chapters that together cover theoretical background and empirical research. These chapters will accompany the reader in understanding **why** this research topic was selected, **what** will be studied, and **how**: with what tools and methods, arriving in the end to results obtained and their implications.

Chapter 1 (Introduction) explains the relevance of this study and its objective. This part focuses on why the topic was selected, what value potential discoveries of this thesis may bring.

Chapter 2 (Literature review) covers the theoretical background and is structured in the following way: at first, the most influential behavioral models, which are conceptualizing how the behaviors are formed, will be discussed. The goal here is to understand what components generally play role in the decision-making. After that, the perspective will be expanded and shifted from rational influences to emotional ones. In particular, the role of emotions in behavioral formation and decision making will be described, the path of worldwide research for the last 50 years together with the main discoveries and insights. Then, the focus will be shifted from current emotions to future-oriented ones: Anticipated Emotions. The concept and prior research in the field will be presented. Moreover, we will have closer look at the attempts of researchers to integrate AEs as a construct in existing behavioral models (e.g. MGB framework). Further on, this chapter will present existing evidence that AEs effects are not always the same, and may depend on the context, object, and subject of the decision. At the end of this chapter, you will find a brief conclusion and state-of-the-art for research in AEs.

Chapter 3 (Research question and conceptual model) starts by highlighting gaps in this state-of-the-art. Generally, the empirical research of this dissertation was build following the traditional scientific research framework: based on the gaps in the literature, the research question was formulated. To help answer this question, a conceptual model was developed, result objectives and hypothesis to be tested were proposed. This chapter clarifies what theoretical concepts were embedded in the conceptual model. Based on the model, nine research hypotheses representing relationships between variables were formulated.

Chapter 4 (Methodology) explains how these hypotheses will be tested. The main tool adopted to evaluate the conceptual model is the survey and after data through the survey is collected, there is a need to process it. Therefore, this chapter includes two blocks: survey development and data processing approach selection and description. The first block explains what measures and scales were selected for every model construct and how the survey was structured, distributed, and managed. The second block clarifies why PLS-SEM methodology was selected as the most convenient data processing tool for this study, describes the basic logic behind the algorithm and indicators that will be used to evaluate the reliability and validity of the conceptual model, and the relationship between constructs.

Chapter 5 (Results) reports the results obtained by adopting the abovementioned tools. At first, the demographic profile of the respondents is reported, and questionnaire reliability checked performed. Then, after a brief note on how SmartPLS software was set up, the focus is shifted to the conceptual model evaluation results. As PLS-SEM methodology suggests, the analysis reports measurement (or outer) and structural (or inner) model evaluation. Results are presented for both datasets (luxury and necessity goods) separately in order to capture good typology specificities and in the end, multi-group analysis is performed to evaluate the significance of differences between groups.

Chapter 6 (Conclusions and discussions) concludes whether the research objective was achieved and briefly clarifies how. Moreover, results are interpreted in the light of the literature review by explaining with what prior opinions this work agrees and disagrees. This chapter also includes implications of obtained findings for academics and managers by highlighting answers to the questions that were never answered before and summarizing practical insights.

Chapter 7 (Limitations and future work) includes the reflection on possible improvement points of the study and provides suggestions for further investigation in the field of Anticipated Emotions.

Chapter 2.

2. LITERATURE REVIEW

The literature review describes prior research done in the field of consumer psychology starting from the 1970s to-80s. The goal of this review is to get to know the state of the art and analyze the efforts of researchers from all other the world in the attempt to understand *how consumers behave and make their decisions*.

This review can be divided into three main blocks. Firstly, the description of the most influential behavioral models: Theory of Reasoned Action (TRA) and its extension – Theory of Planned Behavior (TPB), which are conceptualizing how the behaviors are formed.

Secondly, we will move on to discussing the role of emotions in the process of behavior formation: scholars have realized that apart from rational reasons there are irrational components that affect individual choices. This part will describe major conclusions on emotions made over the last 50 years by the worldwide research community, highlighting the ones particularly relevant for business and marketing applications.

Finally, the concept of Anticipated Emotions will be introduced and discussed in detail. Not only current feelings are relevant for behavior-formation, but also anticipation and savoring could play a great role. In this block, the attempts to include Anticipated Emotions in existing behavioral models will be introduced. For example, the Model of Goal-Directed Behavior (MGB), which was build based on the abovementioned TRA and TPB by including Anticipated Emotions as one of the new model constructs. Moreover, this block will include prior research done in the field of Anticipated Emotions and discuss the differences in emotional responses, since the effect of emotions on behavior formation depends on many contextual factors.

Throughout the literature review, we will not only understand the path researchers made over the last 50 years in the field of consumer behavior regarding emotions but also highlight and connect their major conclusions. Moreover, some controversial questions will be raised.

At the end of this chapter, *gaps* in the current state of research worldwide regarding Anticipated Emotions would be presented as well as research opportunities, based on which, the objectives of this thesis work will be formulated.

2.1. Behavioral and Decision-Making models

Throughout decades researchers were trying to explain the behavior of individuals and how decisions are taken.

It's worth starting the discussion with having a look at the most influential model in the field of consumer behavior and persuasion in general – Fishbein's and Ajzen's model of reasoned action (Fishbein M. & Ajzen I., 1980). Describing and understanding this model in detail is crucial for further empirical research development.

The theory for the last few decades has been leading in the field of social psychology and extremely influential among researchers: the search of citations will reveal over a hundred thousand citations can be revealed overpassed years. Despite age, this model remains very useful nowadays, building a solid base for predicting the behavior of individuals.

2.2.1 Theory of Reasoned Action (TRA)

In the early 70s Martin Fishbein, the initial author of the theory together with his student Icek Aizen were questioning what is driving people into volitional behavior. Back then there was a very weak correlation between attitude and voluntary behaviors. This area of opportunity gave them the motivation to discover what drives behavior which has lead them to creating the Theory of Reasoned Action (TRA) that appears to predict not only consumer intentions and behaviors but also provides a simple suggestion on how to attempt behavioral changes to target consumers.

The TRA model helps with understanding the links between beliefs, attitudes, intentions, and behavior. Before deep-diving into the theory itself, it is important to briefly define basic concepts the theory uses:

• *Belief* is the probability that an 'object' has an 'attribute', normally the belief that some action or some behavior will lead to some consequence.

• *Attitude* is the evaluation of a certain object

• *Intention* is the readiness to perform some behavior or the subjective probability of performing it.

Martin Fishbein together with Icek Aizen started with the assumption that *behavioral intention* often leads to *behavior*: if an individual intends to do something, he or she will probably do it. This connection is rather intuitive. For example, if one was to set as a goal for their New Year Resolution to apply for their dream Master's program at Politecnico di Milano, most probably he or she will be committed to it. In this example, the behavioral intention is represented by the goal while the behavior is whether the application process will be fulfilled or not.

Intentions are generally strongly correlated with the behavior itself, but it is important to remember that this thesis is focusing on volitional behavior – the one that is performed voluntarily and that the individual himself can control. In the aforementioned example, the applying individual does not have control over Polimi's admission process – this is the job of the selection committee. That is why the example is focused on the decision to apply for a Master's and not on the admission itself.

Once the importance of volitional behavior and the strong link between behavior and intention for the topic tackled by this thesis were defined, it is time to move towards understanding: what drives the intention itself?

For understanding the triggers behind the intention, Fishman came up with several different factors: firstly there are **attitudes**, which can be seen as *beliefs about the outcome of the behavior* and can be formed by answering questions such as: "Will it impact one's life?" "What outcomes performing this behavior will bring?"

The authors of the TRA moved even further and realized that individuals do not only need to envision outcomes but also feel that those outcomes will be beneficial for them. To evaluate the impact of the outcomes of behaviors on how one feels, the following questions require an answer: "Will performing the behavior impact one's life positively or negatively?"

Taking the example of applying for the Master of Science program: if one thinks that this action will make their life better, broaden their horizons and lead to even more opportunities, they will very probably form a positive attitude about the behavioral intention of applying for it.

Apart from attitudes, there is another important component that affects intentions which are **subjective norms** - *beliefs about the desirability of the behavior*. Defining this component is facilitated by answering questions such as: "Will other people like that?" "Will one's behavior be approved by others?"

When it comes to applying for a Master of Science, this action is generally perceived by others as a good thing since higher education is valued by society. Subjective norms are mainly focused on the social desirability and acceptability of the behavior one is ultimately trying to achieve. However, is the opinion of people around always taken into account by individuals before making a decision?

Individuals are mostly concerned about the opinions of specific people: family, friends, the ones they care about, not the whole society. That is why in the model subjective norms are formed by beliefs that *the behavior is desirable to specific others*.

Before deciding whether to apply for a Master of Science, one might consider: *"Does my mother think it is a good decision?" "Does my partner think it is a good idea?" "What would my friends say?"*

If some important people for the decider would think that a Masters in Politecnico was going to slow down their development, lead to a wrong path in life and even start voicing those opinions, the person thinking about applying might start feeling worried about whether their decision will be approved or not. On the contrary, if someone's circle would entirely support the decision, it would have a positive effect on their intention to apply.

Another representative case of how subjective norms work and what importance they have can be found in Africa. Individuals are petrified to get HIV tested because the community strongly rejects HIV-positive people. So, the fear of potentially being rejected by their family and community forms their intention not to get tested at all.

To be mentioned that an important component of subjective norm is the motivation to comply with the beliefs of others. For example, even if someone's friends are skeptical about continuing education after a bachelor's degree, but that person's motivation to comply with their opinion is low, the impact of those perspectives on the intention will be insignificant or, even, zero.

The general logic of the model can be summarized schematically:

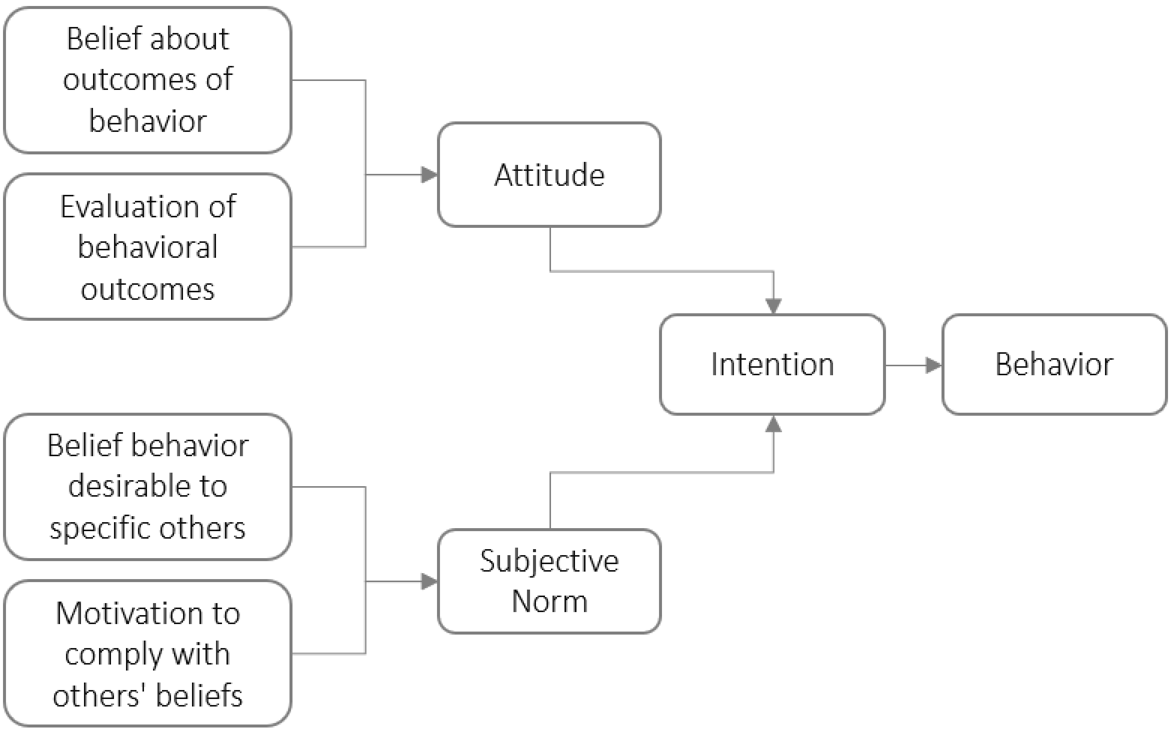


Figure 2-1. Theory of Reasoned Action (Fishbein M. & Ajzen I., 1980).

The theory of reasoned action can be also analyzed from a mathematical viewpoint, under the form of an equation, where the behavioral intention is a function of attitude and subjective norms, considering the weight of each component:

$$\boldsymbol{BI_i = \; w_1 \, A_i + w_2 SN_i}$$

$where$

$BI - Behavioral\ Intention$

$A_i - Attitude\ About\ Perfoming\ the\ Behavior$

$SN_i - Subjective\ Norm\ About\ Performing\ the\ Behavior$

$w - How\ important\ the\ component\ is\ to\ the\ individual$

Despite the form of model representation, the most important logic behind is that behavioral intention is the result of the combination of attitude and how important the belief is, together with what specifically other people might think about it, and how important that is.

With the example of an application for a Master of Science in Politecnico di Milano: even if some of the decider's friends were skeptical about it, thus impacting the subjective norm parameter negatively, if the attitude mattered the most, after overweighting the subjective norm component, the decision of performing that behavior would become obvious.

Later authors completed the theory with even more clearly mathematically defined Attitudes and Subjective Norms.

The function reveals that *Attitudes* equals the sum of belief strength multiplied by outcome evaluation for each of those beliefs:

$$\boldsymbol{A_i = \sum b_i \, e_i}$$

$where$

$A - Attitude$

$b_i - Belief$

$e_i - Evaluation\ of\ the\ Outcome$

Individuals may have many beliefs (b) about any behavior: let's take for example doing sports. While thinking about performing a practice, many things might pop up in one's head, such as the belief of losing weight, becoming stronger, sweating, experiencing physical tension, even, pain. For each of those beliefs, strength is also assigned by analyzing how impactful each belief will be on the outcome. For example, one could be very sure that performing a daily run will bring a loss of weight, thus impacting the attitude in a certain direction.

At the same time, one could consider that daily practices could be painful and even lead to injuries. Depending on the degree of certainty behind these particular negative beliefs, they can influence the attitude more or less.

After envisioning possible belief outcomes, for each of them, according to the TRA model, individuals assign outcome evaluation (e): "Do I personally like or dislike this outcome?"

Sticking to the sports example, one could clearly say that they value the outcome of becoming stronger and healthier and see it as a positive thing. On the contrary, the possibility of getting an injury does is perceived as something negative.

By multiplying each belief strength (the degree of certainty) by the outcome evaluation, which will assign each belief a positive or negative value, and summing up the result across beliefs, it will lead to the computation of the score of an attitude for a particular behavior.

Considering Subjective Norms, mathematically they can be defined as the sum of normative beliefs multiplied by the motivation to comply with each of them:

$$\boldsymbol{SN_i = \sum NB_i\, MC_i}$$

$where$

$SN - Subjective\ Norm$

$NB_i - Normative\ Belief$

$MC_i - Motivation\ to\ Comply$

It is important to note, that unlike the case with an attitude where each belief was summed up when it comes to subjective norms there are considered only the beliefs of specific important people for specific behaviors.

While thinking about whether to start doing sports or not one will consider the opinion of their parents, spouse, friends, or doctors. These are people whom opinions are generally valued when it comes to performing the behavior of starting an exercise. These people are important, thus influencers from a subjective norm perspective. For each of them, the model suggests assigning two values.

The first one is Normative Belief (NB). The value one could get by answering the question: “Do I believe my husband/doctor wants me to start doing sports?”. The numerical value can be assigned to this Normative Belief by ranging the answer on a scale from 1 to 7 (1 – very unlikely, 7 – very likely).

If someone is very sure that their doctor wants them to exercise – they will assign a value of 7 since the doctor’s opinion on health is important. However, if someone’s friend is concerned that by doing sports, they will have less time to spend with their family, this normative belief could be assigned a 3 or 4.

The second value that has to be considered is the personal *Motivation to Comply (MC)*. "How much does one comply with what a particular person thinks they should or should not do?"

Once again, only important people are considered here, the ones whose opinion is valued. But they can be valued regarding specific questions to a different extent. For example, a doctor understands health-related issues better than a friend, so one will want to consider the doctor's opinion about performing sports to a greater extent than their friend's opinion.

To mathematically define it, a scale from 1 to 7 is used for expressing the extent to which one would value the belief of specific other people. By multiplying those numbers and summing up the results across beliefs, we will obtain the numerical value of the Subjective Norm. According to the literature, there are two types of Subjective Norms: injunctive and descriptive.

Injunctive Norms are about one's considerations: "What a person thinks others think they should behave?", they are about one's assumptions about how other people will evaluate them. One could question: "I think others think I should wear a mask/ get vaccinated/ wear a helmet while skiing/ etc." This is about what others think one should do.

Descriptive Norms are about one's own beliefs about what others would actually do if they were in the same situation and not what they would say after a specific behavior. In terms of descriptive norms, one would question: "What do I think most people will do in a similar situation?" They are about personal perception, even though the truth might be different.

It is easier to understand taking the example of wearing a mask. The injunctive norm says: "Most experts want people to war it" Doctors, colleagues, the public want people to do it". Therefore, one would form an injunctive norm that surely says: "Others think I should wear a mask".

At the same time, while looking around in the park and noticing that other people do not always wear a mask can form in one's head a descriptive norm, the belief they have created by describing the environment around them. This will also influence one's decision whether to wear a mask or not.

To sum up the whole model, intentions are a function of attitude: *"Do I think a particular behavior is a good idea"?* and subjective norms: *"Do I think others whom I care about think this behavior is a good idea"?*

Application domains of TRA

The model was proven to be very useful and efficient in practice. The earliest application and wide adoption for TRA were found in the healthcare setting, specific examples are the health campaigns, focusing on STDs, HIV, or anti-smoking campaigns attempting to change behavior by affecting subjective norms and presenting smoking as something socially undesirable.

Wide adoption in the marketing field was present as well. For example, in advertising, when the coupons for a free item were introduced and started to change consumer behavioral intention to enter a shop or restaurant they have never been to and would never consider entering without a coupon.

Limitations of TRA

Like all models, TRA also has some **limitations**. The first one is that TRA only looks at behavioral intentions without considering what are the final goals – specific behaviors individuals plan on executing (*goal intentions*). For example, the intention to lose weight can include the goal intention to eat better, balance nutrition or, start doing sports. However, TRA does not consider that.

The second limitation is the *difference between Intention and Expectation*. Individuals might intend to do something but do not expect to do them successfully. For example, the intent to buy a lottery ticket. Do people generally expect to win? – not much, although they will still give this intention a shot.

The third, very crucial limitation is that *the available choice affects people intention as well as the role of intention on behavioral performance*. Let's take an example of McDonald's': it is available and low-cost in the urban environment, which is one of the reasons why many times individuals make bad food decisions. Accordingly, the available choice will often affect whether individuals will intend to do something and if what's available is indeed limited, their intention will simply not matter. Someone might choose to eat better, but then the monetary side of the question will constrain them in doing that. If one does not have access to any other cafeteria rather than McDonald's in their neighborhood and they live without a kitchen, then this limitation becomes a weakness in their ability to execute the behavioral intention.

Volitional behavior

It is important to keep in mind that the theory of reasoned action has the full focus on **volitional** behavior – the one performed voluntarily. Some behaviors cannot be controlled, and some are enforced. These theories will not predict those behaviors and predict only the ones an individual will or will not perform voluntarily.

Regarding the example mentioned above about applying for the Master's program: the decision of whether to apply or not is entirely the individual's to take. However, whether the individual will actually study there or not is not up to him / her: the selection committee will take a final decision. An individual can intent to prepare more and work on their application better, but they do not have control over whether they will be accepted or not. So, the intent to apply is a volitional behavior, while being accepted is not.

Another representative example is marriage. An individual can have plans to get married in the next five years. It can be strong and clear intent. However, it takes two people to get married, therefore it is not completely under the control of an individual.

2.2.2 Theory of Planned Behavior (TPB)

According to the limitations and based on the critique of the very first model presented - TRA the theory has been improved and extended. Ajzen wanted to create the universal method for designing successful behavioral change intervention and continued the research dealing with various aspects of the critiques and limitations introducing the theory of planned behavior (TPB) (Ajzen, 1985b, 1991; Ajzen & Madden, 1986). This theory allows dealing with behaviors that are not entirely under one's volitional control.

There is one major difference introduced in the theory of reasoned action model, compared with the current, more recent version - the theory of planned behavior. It is the addition of the 'perceived behavioral control' component, which describes the belief of an individual to be capable of doing the behavior, underlines the self-efficacy.

In the mathematical form, the new component presented similarly as attitudes and subjective norms were.

$$\boldsymbol{PBC = \sum C_i P_i}$$

$where$

$PBC - Precieved\ Behavioral\ Control\ or\ self - efficacy$

$C_i - Control\ Beliefs$

$P_i - Power\ of\ Control\ factors$

Perceived behavioral control (PBC) is a function of two components: control beliefs and factors. *Control beliefs* reflect whether one believes certain things could be an obstacle or not. When it comes to doing sports, some might think that they can perform exercises only with equipment or they believe that sports can be done only with a coach.

These beliefs are influencing one's idea of how much control they have over the decision to start exercising. Maybe, someone simply does not have money for a coach, or, live in a dormitory without access to professional equipment.

To measure how powerful each of those beliefs is, the second component is introduced in the model: the *power of control factors.* If one is very sure that without the equipment it is not possible to do sports at all, this belief will have high power. By multiplying those factors and summing them up across all control factors, the result is a value of perceived behavioral control.

In the schematic form, the general logic of the TPB is summarized in figure 2-2.

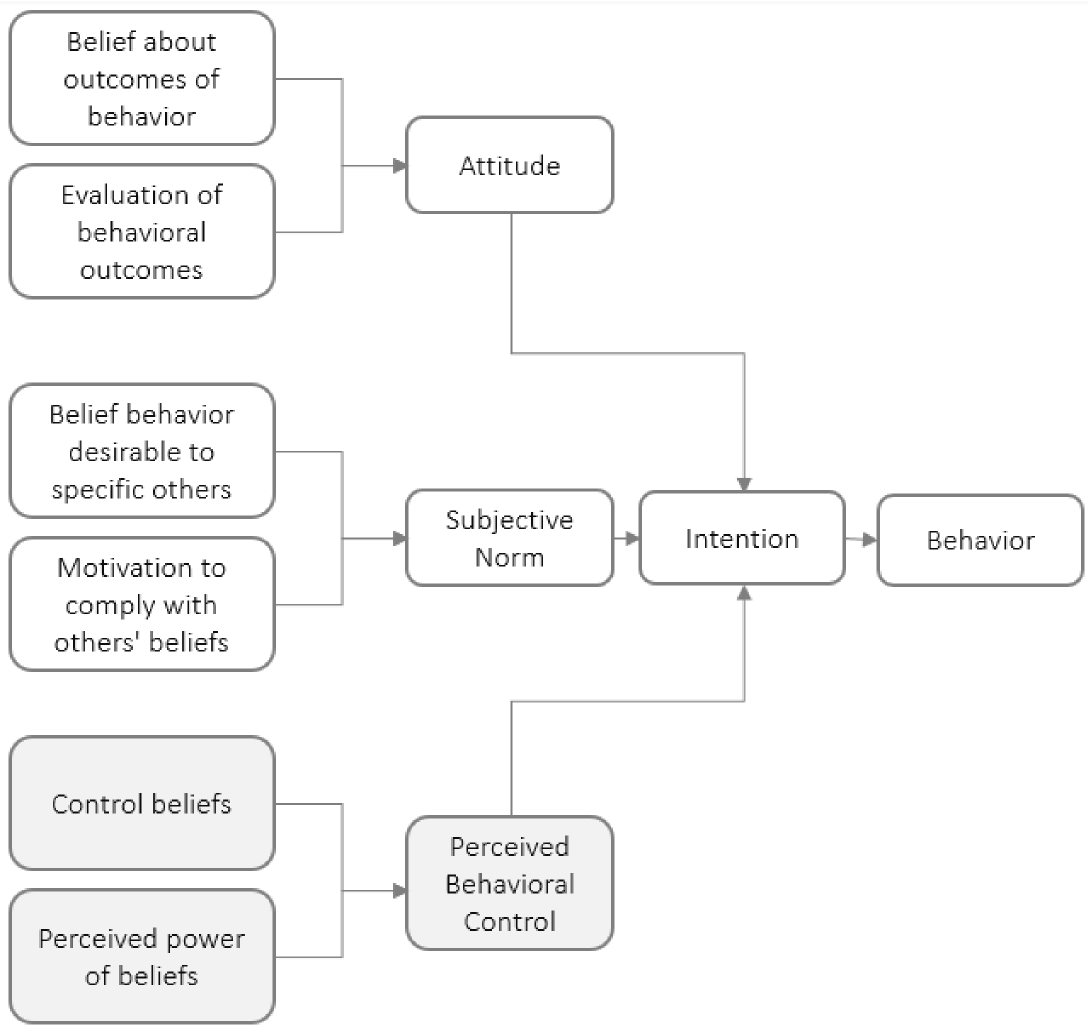


Figure 2-2. Theory of Planned Behavior (TPB) (Ajzen, 1985b, 1991; Ajzen & Madden, 1986)

Perceived Behavioral Control parameter allows including some behaviors that could not be covered by the Theory of Reasoned Action and that are not entirely under volitional control.

For example, even the simple consumer decision of whether to start buying more fruits and vegetables is not entirely volitional. In some regions, those products are simply not accessible, or, costly. Maybe, the consumer lives together with parents, who do the shopping and control the family diet. Perceived Behavioral control parameter allows enlarging the scope of decisions the model can work with and improve its predictive power.

The extended theory has an even broader application and provides step-by-step guidance on how to design a successful behavioral intervention.

Even if TRA and TPB seemed to perform well, a recent meta-analysis examined 142 empirical tests of the models and found that the TPB accounted on average for 40% of the variance in intention and 29% of variances in behavior (Armitage & Conner, in press). Although there is little question about the predictive abilities of TPB, it is sufficient for it to be questioned. From the moment TPB was published, many researchers have tried to deepen and broaden this model, some of which will be discussed later in this chapter.

2.2 Role of emotions in behavior formation

After getting familiar with the initial widely accepted logic behind decision making, it is time to ask ourselves the question: do emotions play role in it?

For a long time, the scientific community relied on the assumption that consumers aim to make decisions as *rational* as possible: aiming to buy the best product for the best price, etc. When individuals make purchase decisions, they consider so many factors: “Will the product meet their expectations? Is this price fair? Is it the best time to buy or better to wait for sales?”

For example, one can find a great offer for a product: let’s say, an extraordinary discount due to temporary promotion (e.g., for a new laptop or TV). Many consumers want to take advantage and save money, thinking that this decision will make them feel good, satisfied, and proud that they catch such a great deal. In this case, not purchasing the product now will make them unhappy later. On the other side, maybe a better offer will appear later, and they would regret buying it with a higher price now. Sometimes, the purchased item can turn out to be worse in quality or useless for the consumer: can simply not meet their expectations at all, which will also lead to negative feelings. By not wanting to experience negative emotions in the future, consumers may reject even the most extraordinary offers.

Nowadays it goes without saying that emotions are influencing purchase decisions, but there is a long path researchers made to arrive at this point. Only recently attention to the role of emotions in economic and marketing decisions increased.

To understand better the relationship between emotions and behaviors, let's have a look at the primal research done in this field and highlight the main discoveries, especially the ones relevant to the marketing field.

From the meta-analysis in the field of decision making by Jennifer S. Lerner and colleagues (Lerner et al., 2015a) it is clearly visible that attention to the emotional effects started to grow only in the 21st Century (Figure 2-3). In economic decisions the role of emotions very rarely was mentioned for most of the 20th century, the majority of decision models were based on rationality. Over the past decades, it became clear that to rational choices we should add situational and cognitive effects and the role of emotions in decision making should be specified. We can see that from 2004 to 2007 the number of papers being published yearly doubled as well as from 2007 to 2011.

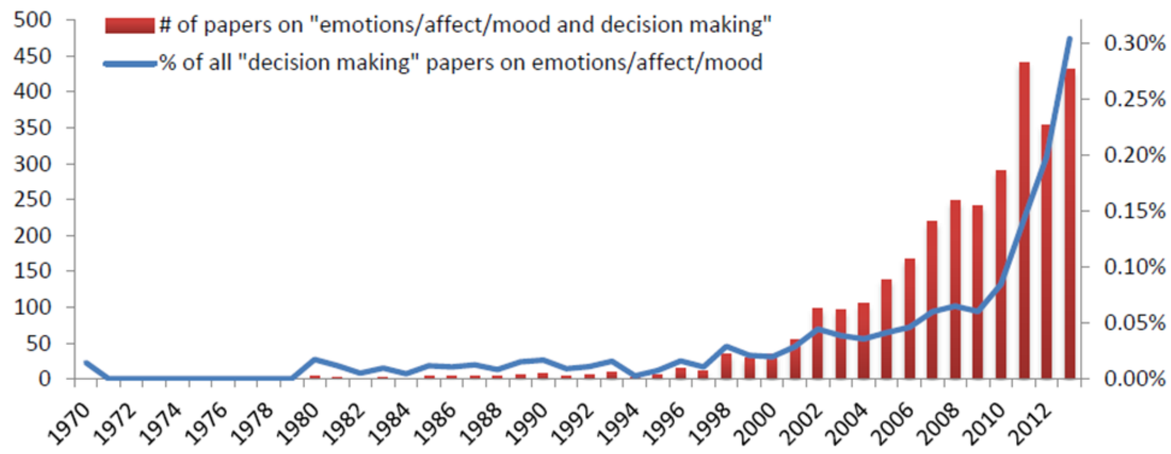


Figure 2-3. Number of scholarly publications that refer to "emotion(s)/affect/mood and decision making" (in red bars) and percentage of all scholarly publications referring to "decision making" that represents. (Lerner et al., 2015a)

The particular attention was also drawn not only from economists but also from psychologists and many scientists who concluded that emotions are the dominant driver for the majority of meaningful life decisions. (e.g., Ekman 2007, Frijda 1988, Gilbert 2006, Keltner & Lerner 2010, Keltner et al 2014, Lazarus 1991, Loewenstein et al 2001, Scherer & Ekman 1984).

Many researchers admitted the role of emotions in goal-directed behavior: it became clear that emotions have important implications for behavior in the sense of providing impulses to action (Plutchik, 1982) or stimulating approach or avoidance tendencies (Mehrabian & Russell, 1974).

One of the first theories was developed in 1987 by Oatley and Johnson-Laird - the communicative theory of emotions (Oatley, 1988), the approach to study better emotions in goal-directed behavior.

According to the study, the important function of emotions is to *communicate* to one's cognitive system or to other people which part of the goal structure requires attention. The theory proposes that the main function of emotions is to assist decision-making in an uncertain world with thousands of possibilities. Our brains simply can not process and consider all the numerous outcomes. Taking into consideration the limited resources of organisms in the management of multiple goals and unlimited outcomes, we have emotions to help us navigate.

Authors discovered that positive emotion usually led individuals to a decision to continue with the current behavior, while negative emotions are associated with failures and problems to achieve desired goals. As a result, existing goals-structures are revised due to problem-solving activities, and new plans are developed to deal with problems.

A similar approach is present in the *dynamic theory of emotion episodes* by Stein and associates(Stein et al., 1993). The theory states that changes in the status of valued goals result in emotional experiences. Emotions evoke goal-directed behavior with an aim either to maintain reaching the desired outcomes or avoid receiving undesired outcomes. As a result of different appraisals, different emotions can appear.

For example, people experience happiness when an event establishes the certainty of goal success, while sadness will be evoked if an event signals a failure of a goal. New goals are generated to maintain or change behavior depending on the emotion itself and the nature of the event by which it was evoked. This process is dynamic and new events are generating new cycles of emotional experiences that will lead to problem-solving and planning activity in a continuous sequence: goal-action-outcome.

Another study by Frijda (Frijda, 1987) investigated in-depth the connection of emotions to behaviors. The author has shown that emotions can be described both in terms of action readiness (such as attending, rejecting, moving towards, moving against, etc.) and situation appraisals. The key message was that ''events are appraised as emotionally relevant when they appear to favor or harm the individual' s concerns: his or her major goals, motives, or sensitivities'' (Frijda, 1989). Moreover, Frijda mentions the possibility of the impact of emotions that could or will occur (anticipated emotions), however, it was not discussed in detail in his works.

2.2.1 Integral and Incidental emotions

Talking about emotions, it is important to make the distinction between Integral and incidental ones.

- Incidental emotions are the ones we carry with us to the decision that has *nothing to do* with the decision and normally should be irrelevant to present judgments and choices.

- In opposite to incidental, *integral* emotions are those caused by the decision itself.

Integral emotions strongly influence the decision-making process. They arrive when we think about the potential implications of a decision. A good example could be the anxiety about the potential outcome of the risky decision which will lead to choosing the less risky option.

Another example is donations: while feeling grateful and proud people decide to donate a decent amount of money to a hospital, that at some point helped to cure their loved ones, even though rationally the sum will limit their spending.

Many researchers have concluded that in particular negative integral emotions are a useful guide to decision making. Solomon was stating that anger strongly motivates us to respond to justice (Solomon, 1993)other researches proved that anticipation of regret motivates us to avoid taking risky decisions(Loomes & G. Sugden, 1982)

From another point of view, integral emotions can also represent bias. For example, some people feel afraid to fly on airplanes and prefer driving instead, while it is acknowledged that rates of death by driving are much higher than the ones by flying (G Gigerenzer, 2004).

In any way, we can conclude that integral emotions have a huge influence on individuals even if the rational cognitive information will suggest alternative choices.

Once these emotions are appearing; they are becoming very difficult to detach from target decisions.

Incidental emotions appeared to be very valid as well. Few interesting researchers were conducted on incidental emotions - the ones that should be normally irrelevant to present judgments and choices. We can observe these emotions everywhere around us: if someone fought with a family member at home, he or she might arrive at the workplace full of anger. The professor that was having a really good day, might decide to grade the student higher, etc.

For example, generally, it is assumed that people are happier during sunny days. Economists have found a positive correlation in 26 countries between the amount of sun on a particular day and stock market performance on the same day (Pardo & Valor, 2003)

Another study showed that the stock market performance was worsening when during the World Cup a country's national soccer team was eliminated (Edmans et al., 2007). These studies show the emotional effect on the macro-level and have the potential to be combined with the micro-level models.

2.2.2 Valence-based approach

One of the very common intuition is that all emotions can be divided into positive and negative. Moreover, it is assumed that emotions of the same valence would have similar effects. This approach is called valence-based and had created a solid base for most studies on judgments and effects.

This way people that generally have a good mood and emotions would have more optimistic judgments, while people in bad moods on the contrary are pessimistic (Loewenstein & Lerner, 2003)

For a long time valence was the most relevant aspect of emotions. However, even if more and more studies on emotions in decision-making were appearing, there were no models developed to capture other differences among emotional experiences. In

1998 Mellers and colleagues concluded that a “more detailed approach is required to understand relationships between emotions and decisions” (B. A. Mellers et al., 1998)

The most influential study that went beyond valence was performed by Lerner and Keltner in 2000: ‘Beyond valence: Toward a model of emotion-specific influences on judgment and choice’ (Lerner & Keltner, 2000)

Later on, they presented the Appraisal Tendency Framework (ATF)(Han et al., 2007; Lerner & D Keltner, 2001), which requires specific attention in the discussion of emotions in decision making.

2.2.3 Appraisal-Tendency Framework (ATF)

The ATF attempts to explain why and how emotions that occurred in the past can color future choices and judgments. The framework proposes that particular emotions give rise to particular cognitive processes, therefore affecting decision making.

As mentioned earlier, integral emotions are the ones evoked by influencing subjective events, normally relevant to current choices. For example, anticipated regret while evaluating a risky decision or gambling is affecting our willingness to take risks at all. Incidental emotions encompass the influence of those subjective events that normally should be irrelevant to current choices. A good example is the influence of good or bad weather, listening to different types of music, etc. Those experiences may influence completely unrelated topics and objects.

ATF has been mainly focused on **incidental** influences. Both integral and incidental emotions have a significant impact on consumer decisions, but because incidental influences are hardly noticed by decision-makers themselves. That is why they are a particularly interesting type and ATF could potentially help to control unwanted influences.

One of the most important specificities of ATF is that it goes **beyond the valence** approach. While most of the studies were dividing moods into good and bad. Even In the literature, it was widely accepted that “the only relevant aspect of emotion is their valence” (Elster,1998, p.64)

Indeed, this aspect is very productive to consider: good moods have positive impacts, bad moods - negative. Even though valence has shown to be a very effective dimension for predictions, there are other dimensions to consider while dealing with emotions and ATF was aiming to become a multidimensional framework.

The goal of the study was to find the exact connection between emotions and decisions. The schematic representation of the model (figure 2-4) can help us in further understanding every component and correlations between them.

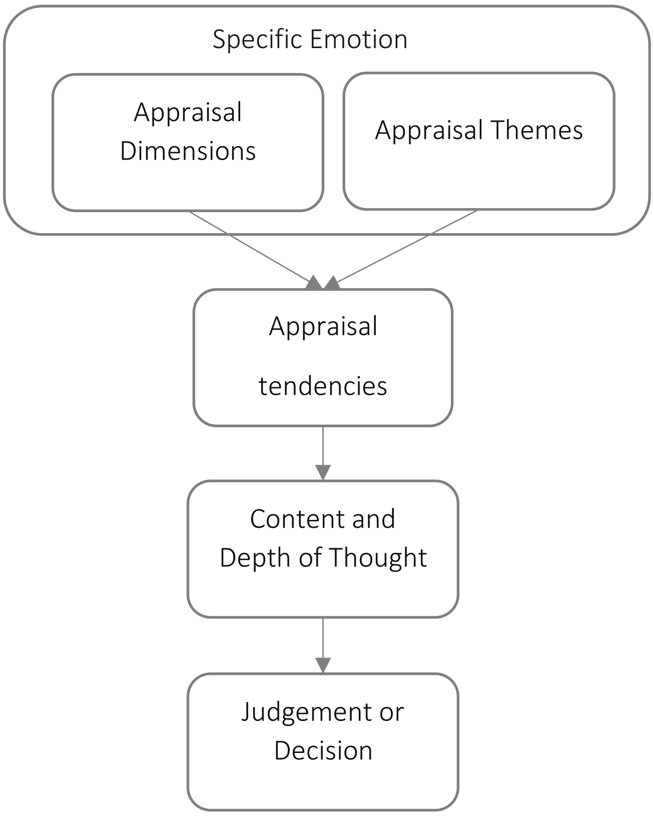


Figure 2-4. Appraisal Tendency Framework (ATF)(Han et al., 2007; Lerner & D Keltner, 2001)

One important dimension to mention is the cognitive **appraisal**. One of the first appraisals theories was developed by Smith and Ellsworth (1985) where six cognitive dimensions were identified:

- pleasantness
- anticipated effort
- responsibility
- certainty
- attentional activity
- control

Above mentioned dimensions provide a basis for contrasting and comparing single emotions. For example, happiness (positive valence emotion) is associated with control and certainty. Fear is associated with uncertainty and situational control over negative events, while anger is connected with certainty about what happened and control for negative events. This way we can see a clear distinction between anger and fear. Moreover, we can also notice that happiness is closer to anger rather than fear. Overall, appraisal patterns appear to be very useful regarding understanding specific emotions.

For a bigger scope, there are also *Appraisal Themes* present in ATF. They represent a summary of harms and benefits that can arise after an individual interacts with the social environment. These appraisal themes are influencing the probability of different courses of action (a concept developed by Lazarus, 1991). For example, sadness appraisal is an irrevocable loss, thus, calls to action to change circumstances by seeking rewards (Lerner et al., 2004).

In ATF Appraisal dimensions and themes from specific emotions are connected with *appraisal tendencies*. In other words, each emotion fuels judgments and subsequent decisions. So not only do emotions arise from decisions, but also give rise to future events depending on appraisal themes and dimensions of a specific emotion.

Table 2-1. *Two illustrations of ATF originally developed by Lerner & D Keltner, 2001*

	Illustration with negative emotions		*Illustration with positive emotions*	
	Anger	*Fear*	*Pride*	*Surprise*
Certainty	High	Low	Medium	Low
Pleasantness	Low	Low	High	High
Attentional Activity	Medium	Medium	Medium	Medium
Anticipated Effort	Medium	High	Medium	Medium
Control	High	Low	Medium	Medium
Others' Responsibility	High	Medium	Low	High
Appraisal Tendency	Perceive negative events as predictable, under human control, & brought about by others	Perceive negative events as unpredictable & under situational control	Perceive positive events as brought about by self	Perceive positive events as unpredictable & brought about by others
	Influence on risk perception		*Influence on attribution*	
Influence on Relevant Outcome	Perceive low risk	Perceive high risk	Perceive self as responsible	Perceive others as responsible

Those appraisal tendencies have two categories of further influence on decisions:

- Content of thought effects
- Depth of thought effects

To demonstrate the influence of the *content of thought effects*, let's take an example of judgments considering the influence of sadness and anger. Sadness goes together with appraisals of situational control, while anger co-occurs with individual control appraisals. Therefore, sad individuals will blame the situation and environment, while angry people will blame other individuals within the environment.

One of the major values of the ATF framework is that it shows that emotional effects occur due to changes in (a) content of thought, (b) depth of thought, and (c) content of implicit goals.

Discussing ATF, it is very important to mention the *matching constraint.* Since ATF is focusing on specific distinct emotions, only judgments related to particular emotional appraisals can be discussed. Therefore, there is a constraint by a match between the cognitive dimension of choice, judgment and appraisal dimension, and themes of emotion.

Overall, ATF is very useful in several research streams, the main are:

- Risk assessment

- Monetary value assessment

For economic and marketing fields, assessing the monetary value of services and goods lies at the core of many consumer decisions. Even if the connection of mood with buying decisions is quite conventional, the effects of different specific emotions are not entirely clear.

Study shows that specific emotions influence our decisions in regards to monetary value assessment. Many other promising research lines go in the same direction

- compassion and pride affect

- disgust - one of the major emotions in the consumer context

To sum up, ATF provides a solid base for predicting the effect of specific emotions on consumer decision-making. The model allows assessing the choices way more complex than the ones based on valence alone. Apprisal Tendency Framework is extremely useful for understanding the role of specific emotions in decision making.

Other researchers investigated similar questions and ATF is sharing some basic principles also with other theories of affect and judgments. For example, the general assumption that affect has a powerful effect on decision-making and behavior even without the awareness of an individual is also present in the Affect Infusion Model (Forgas, 1995) as well as in the Mood as Information Model (N Schwarz, 1990).

Researches went even further in studying the effect of specific emotions on behavior. Lerner with colleagues in 2013 conducted experiments to test whether sadness would increase impatience regarding financial decisions. (Lerner JS, 2013) They hypothesized that sadness will create a myopic focus on obtaining money now instead of later, even if immediate profit would be much smaller than the possible later one. As it was predicted, the participants who were in the sad-state were agreeing 13-34% more frequent to accept less money immediately and avoid waiting than the neutral-state participants. Just a valence-based approach would not allow us to explain this phenomenon: other negative emotions did not have the same effect on the decision and, for example, disgusted participants were ready to wait as well as neutral-state ones.

2.2.4 Other relevant discoveries

Another branch of research emerged from the fact that emotions are social, they are adaptive depends on the influence on interaction partners. Emotional influences can be very complex: for example, people experience happiness from the opportunity to help other individuals without expecting anything in return (Dunn et al 2008). On the contrary, the social aspect of emotions can be used to manage one's bad moods, helping to deal with distress or sadness (Schaller & Cialdini 1988).

Moreover, scholars have discovered that emotions can work as communication systems, they can help people to navigate social interaction by providing additional information. As a result, emotions allow us to build and maintain productive and healthy social relationships (Keltner et al 2014).

Over the years of research, the scholars agree on three main conclusions regarding the role of emotions in interpersonal decision-making (Keltner & Haidt 1999):

- Emotions help individuals to understand one another's intentions;
- emotions incentivize costs on other's behaviors;
- they evoke complementary, shade the emotions on others.

These discoveries are particularly useful and have found much application in the business world. For example, when it comes to negotiations, the expression of anger leads partners to consider a more cooperative strategy since anger plays a role as a signal for behavioral adjustment (Van Dijk et al 2008). Similarly, communicating disappointment with the current business proposal evokes the emotion of guilt in the partner and motivates to adjust the bargaining strategy (Lelieveld et al 2013). In general, increasing knowledge in this field is allowing negotiators to use the emotions of partners as an additional source of strategic information.

Another branch of research is investigating how emotions influence groups and group-level emotional processes. Group decision-making is particularly relevant in the business world. Moreover, emotions affect the performance outcomes: general positivity of the group leads to better performance, unlike general negativity (Barsade 2002, Hatfield et al 1993, Totterdell 2000). There are many research opportunities still present in this area, especially at the level of discrete emotions.

But not always emotions are served to help individuals, in many cases, some unwanted effects can badly affect decision-making. In particular, researchers investigated: "How can we minimize/reduce unwanted emotional responses?"

In theory, the most intuitive strategy would be to *delay the time* of making a decision, since the majority of emotions have a short life-span, at least the physiological responses like facial expressions are quickly fade (e.g., Mauss et al 2005). Of course, it can be argued that all emotions can disappear fast, but the research has shown that individuals revert to the neutral states over time (Gilbert 2006).

Typically individuals tend to underestimate this feature and this is the main reason why this simple and effective strategy of time delay is rarely used. However, the strategy is proven to be effective, all these suggestions "count to 10 in your mind before giving an immediate reply" actually make sense.

Another strategy is trying to reframe the meaning of stimuli that caused a particular emotion. The strategy is called *reappraisal.* Basically, it suggests changing the mindset: for example, to avoid sadness after receiving a lower grade at the exam, reminding ourselves: "it was just a test, there is so much more in life". This approach has proven to be effective in reducing negative self-reported feelings. People adopting reappraisal, in general, have more positive emotional experiences (Gross & John 2003).

The third strategy is to deal with unwanted emotions is *suppression*, something like: "block your anger", "control your fear", etc. Even if this approach is popularized in literature, according to scientific research, suppression is counter-productive. Emotions are designed by nature to help us and attempt to avoid may be effective only in hiding the expression of it, without reducing the subjective experience of emotion itself (Gross & Levenson 1993).

Reappraisal and suppression techniques have a theoretical connection with the content of thoughts from the Apprisal Theory Framework. "Think about that differently@, or, "Don't think about that".

There are other possible solutions that help to detach the decision-making process from unwanted emotions: crowding out emotions, increasing the awareness of decision-maker about misattribution, or, even incentivizing financially to increase the effort of thought. After all, it is clear that taking decisions is not an easy cognitive task, especially considering the emotional aspect.

The managerial application of these discoveries and proposed strategies is quite broad. Although, implementing them requires time and in the business world the important decision-makers are always busy. By Thaler & Sunstein in 2008 alternative method was proposed: *choice architecture*.

The authors offered a set of tactics to affect behaviors automatically by framing and structuring choices without restricting them. For example, in 2003 (Thaler & Sunstein 2003) they suggested to cafeterias organize menus so that healthy food is the first thing consumers see. Usually, we arrive at the cafeteria hungry and the effort of choosing food takes time, so we go for mindless consumption neglecting sometimes our goals to eat healthier. Healthy food at the beginning of the menu was encouraging healthy choices. This case is demonstrating the power of choice architecture in setting god defaults. To sum up, when people can rely on accessible clues, the average decision-making quality will be improved as a result.

The application of the choice architecture is very broad and the technique works quite well in reducing the effect on immediate emotions. For example, in Italy marriage application consists of two steps: the first time you come to make a "Publication" and even if you are fully checked and eligible, the date for actual marriage you are allowed to choose only after 12 days. In the U.S. there is a mandatory waiting period to buy guns, which helps to deal with the affects of temporary anger.

2.2.5 Main conclusions over last 50 years

To conclude the analysis of the primal research work in the field of emotions in decision-making, let's sum up the major discoveries made over the last 40 years:

- Emotions are very powerful drivers for decision-making that can be predicted. Their effects are neither random nor phenomenal and the mechanisms through which emotions influence choices can be described.

- There are incidental and integral emotions. The incidental ones frequently produce undesirable influences.

- Theories that go beyond valence have proven to be more effective than the ones focusing only on positive versus negative distinctions.

- Emotional effects occur mainly in the changes of three mechanisms described by the Apprisal-Tendency Framework: the content of thought, depth of thought, the content of implicit goals.

- When emotions are unwanted for the decision-making process it is very difficult to avoid them. However, few techniques are proposed, among which there are reappraisal, time delay, suppression and, the most promising one: choice architecture.

- The field of emotion in decision-making is fast-growing and is 'far from mature' (Lerner et al., 2015b) and every new appearing study is rising even more questions that have to be answered.

Nowadays it is clear that the link between emotions with behavior and decision making is very strong and in order to increase the quality and predictive power of behavioral models, emotions should be introduced.

Before we move towards combining emotional and rational factors in behavioral models, one very important concept: anticipated emotions has to be introduced and discussed.

2.3 Anticipated emotions

As we understand nowadays, emotions are tremendously relevant for decisions and judgments. Many researchers keep their focus on the *current* feelings to get informative clues for predicting judgments (e.g. the feelings-as-information theory by Schwarz, 2012), ignoring anticipation of the affective consequence of current decisions.

When we think, for example, about purchase decisions, in the end, the key personal input is whether purchasing or non-purchasing will make us feel better.

Some scholars had shown that emotions that we expect to experience in the future are driving the decision-making process (Barbara A. Mellers & McGraw, 2001) this is why the majority of marketing communication is focused on showing the expected outcome of the purchase decision. "This product will you feel special, exclusive, fulfilled, etc."

During the last two decades, studies on discovering the effect of anticipated consequences started to appear. These effects are present in a broad variety of contexts and especially relevant for the marketing field. The special role in the decision-making process plays anticipated emotions.

2.3.1 Concept of anticipated emotions

Usually, our decisions have the ultimate goal to bring us happiness and avoid unhappiness. In psychology research had shown that individuals are seeking pleasure and trying to avoid pain(Higgins, 1997). Following this logic, anticipated emotions can serve as simple informative clues in decision-making.

In the literature, anticipated emotions are described as a kind of prefectural thinking where an individual imagines the affective consequences of goal achievement and goal failure before deciding to act(Perugini & Bagozzi, 2001a).

For simplicity, Anticipated emotions can be seen as the answer to the question: "How would you feel when the decision for alternative X leads to consequence Y?" In short:

***Anticipated emotions* – perceived consequences of goal achievement and goal failures.**

Similarly to the discussed earlier current emotions, anticipated emotions can be classified by valence (def. By Perugini and Bagozzi, 2001):

- *Positive Anticipate Emotions (PAE)* – represent positive feelings about the possibility of goal achievement in the future.
  Examples: Happy, Glad, Excited, Satisfied, Delighted, Content
- *Negative Anticipated Emotions (NAE)* – represent negative feelings arising from the impossibility of goal achievement in the future.
  Examples: Disappointed, Sad, Uncomfortable, Anxious, Angry, Frustrated, Nervous, Agitated.

Table 2-2. *Positive and Negative AEs.*

Positive Emotions	*Negative Emotions*
Excited	Angry
Delighted	Frustrated
Happy	Guilty
Glad	Ashamed
Satisfied	Sad
Proud	Disappointed
Self-assured	Depressed
	Worried
	Uncomfortable
	Fearful

To understand better the concept, let's analyze primal research regarding anticipated emotions starting with the attempts of different scholars to define them and specify the role in behavior formation.

2.3.2 Integration of AEs to behavioral models

After getting familiar with the concept of anticipated emotions, the logical step will be to deepen understanding of the role of emotions in terms of impact on behavior. To do that, let's make a step back to the behavioral theory described at the beginning:

Theory of Reasoned Action (or extended Theory of Planned Behavior). When the effect of Anticipated emotions became clear, scholars started to attempt to improve and extend initial TRA and TPB with the emotional aspects.

The earliest consideration of anticipated emotions in behavioral models was done by Parker et al. (1995). They found that anticipated regret tempered behavioral expectations Most early studies were focused particularly o negative anticipated emotions. Another example is the study by Richard et al. (1995), who found that anticipated post-behavioral affective reactions measured with `worried / not worried', `regret / no regret' and `tensed / relaxed ' items mattered in the context of refraining from sexual intercourse and condom usage.

Generally speaking, there are two approaches for revision of any theory:

- *Theory broadening* when by specifying processes formally contained in error terms during tests, more variance can be accounted.
- *Theory deepening* by introducing new variables to explain better how existing predictors influence each other. The main idea of this approach is that by introducing a new mediating or moderating construct, the theoretical mechanisms behind the model can be better understood.

The first research present in this direction of expanding TPB was introduced by Perugini and Bagozzi's in 2001 (Perugini & Bagozzi, 2001b) Authors were broadening and deepening the theory of planned behavior. As a result, the Model of Goal-directed Behaviours (MGBs) was introduced.

2.3.2.1 Model of Goal-directed Behavior (MGB).

The authors used the abovementioned theory deepening approach and introduced a new construct: Desires as a proximal cause of intentions. Moreover, they suggested adding anticipated emotions – perceived consequences of goal achievement and goal failures, as determinants of desires. All other traditional TBP antecedents (subjective norms, attitudes, and perceived behavioral control), according to the new perspectives, should work through desires. (Perugini & Bagozzi, 2001b). Visually the theory is conceptualized in figure 2-5.

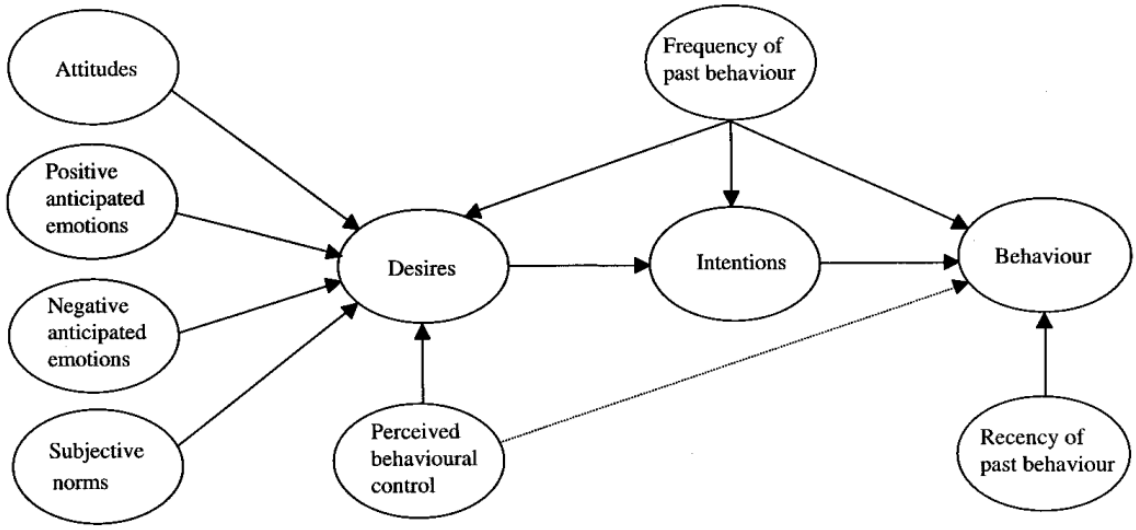


Figure 2-5. The model of goal-directed behavior. (Perugini & Bagozzi, 2001b)

The MGB posits that desires have a direct influence on intentions and transform the motivational content to act, specifically: attitudes, anticipated emotions, subjective norms, and perceived behavioral control:

Desires = f (attitude, subjective norms, positive and negative anticipated emotions);

Intentions = f (desires).

Another predictor for desires is the Frequency of past behavior, which is also assumed as a predictor of intentions and behavior. Another component - recency of past behavior is assumed to be a predictor for behavior only. The main goal is to broaden TPB by 4 the introducing of anticipated emotions and by including new decision criteria. Frequency and recency of past behaviors were introduced to incorporate information concerning automatic aspects that are not reflected by existing variables of TPB.

The authors highlight three important differences between MGb and TPB. Firstly, in TRA and TPB, the attitude was mainly focused upon what one does or can do, while in MGB the specification of anticipated emotions focuses not on action itself, but on achieving personal goals. In this way, it is taken into account that there are emotional consequences of both goal achievement and goal failure. So, the decision-maker is affected by these “prefectural apprisals” (Gleicher et al. 1995).

The second difference refers to the theoretical concepts behind attitude towards an Act and anticipated emotions Attitude is a disposition to respond favorably or unfavorably and usually arises from learning. After making a decision, a person's reaction is attached to him or her for some time, and with more decisions made, comes more learning, which forms the attitude. Once attitude is formed, or, better to say: “learned”, it is triggered automatically when one is exposed to an Act or object, or just thinks about it (Fazio, 1995). On the contrary, processes behind anticipated emotions are more dynamic: first, an individual has a goal, only after that the consequences of accomplishing on not accomplishing this goal apprise and correspond to the emotion raising: positive or negative.

In other words, while attitude is a constant, hardly changeable parameter, authors of MGB theory (Perugini & Bagozzi, 2001c) propose a concept of anticipated emotions as something more dynamic and context-specific. They make an implicit difference between one’s goal standard value and anticipated consequences of achieving or failing it. Attitudes do not have similar functions and are more disposition-like responses to a particular Act or object.

The third crucial difference occurs at the level of measurement for attitudes and anticipated emotions. Attitudes always used to be measured by bipolar items: favorable vs unfavorable. MGB authors have argued this approach and suggested using unipolar items (e.g. continuum from “not at all” to “very much”) for measuring anticipated emotions. The main argument is that using only a bipolar scale can make the positive and negative effects mutually exclusive and forbid respondents to express differential relevance. In reality, these positive and negative affects can be related or unrelated (positively or negatively) to each other, in different circumstances (Bagozzi, Wong, and Yi, 1999).

To recap, the main differences between concepts of *Attitude* towards act in the original TRA (and TPB) theories (Ajzen, 1985a; Ajzen & Madden, 1986; Fishbein M. & Ajzen I., 1980) and the newly introduced concept of *Anticipated Emotions* are summarized in the table 2-3.

Table 2-3. *TRA and MGB core differences.*

	Attitude in TRA (and TPB)	Anticipated emotions in MGB
Concept	Is a disposition-like tendency to respond favorably or unfavorably towards the action.	Are based on personal goals and function as independent variables based upon a decision process that takes into account judged consequences of goal achievement and goal failure.
Measure	Bipolar items	Unipolar reactions

To test the MGB model, the authors performed two studies. One study was connected with body weight regulation and another one was connected to studying for the exam. Both studies had two phases: first phase respondents provided background information, stated their body weight/ studying goals. At phase 1 participants were not told that later they will be contacted for phase 2. Four weeks later they were asked to fill the survey that measured their behaviors towards achieving goals. After collecting data, researchers tested the model with SEM (Structural Equations Modeling) method.

The results strongly supported the hypothesis made under the MGB model. Desires mediated effects on intentions in both studies. Desires were found to be functions of anticipated motions.

As a result, considering Anticipated Emotions improved significantly the TRA (and TPB) model. However, MGB authors state that deeper investigation is needed to understand the relationship between anticipated emotions and behaviors. (Perugini & Bagozzi, 2001c).

2.3.2.2 Other integration of AEs to TRA

Researches continued to investigate the role of anticipated emotions and one of the recent studies introduced by Steven A. Taylor in 2016 (Taylor et al., 2016)was considering the Role of Affect and Anticipated Emotions in the Formation of Consumer Loyalty and presented the modified Theory of Reasoned Action.

Taylor takes MGB as a starting point. Indeed, one of the most crucial points in the point of view of Bagozzi is that attitudes are synonymous with evaluative judgments; and valenced feeling states unique from evaluative judgments. Bagozzi et al. (1999). This difference underlines the necessity of adding anticipated emotions as a separate construct to the Theory of Reasoned Action.

The main question that still was left unanswered is: “Does explicitly adding Affect and/or emotions as unique exogenous constructs will meaningfully contribute to attitude-based models?” By Bagozzi and colleagues Bagozzi et al. (1999) the concepts behind Affects and Emotions were identified as follows:

- *Affect* is an umbrella term for a set of more specific mental processes including emotions, moods, and possibly attitudes. It is a general category for mental feeling processes, rather than a particular psychological process.

- *Emotion* is a mental state of readiness arising from cognitive appraisals of events or thoughts; it has a phenomenological tone and may result in specific actions to affirm or cope with the state of mental readiness.

As discussed previously, both emotions and affects are important parameters for explaining decision-making and behavior. However, how exactly to include emotions into behavioral models, specifically in attitude-based ones has been a challenge.

Taylor and colleagues have proposed three perspectives of the role of emotions and affects in the attitude models – figure 2-6.

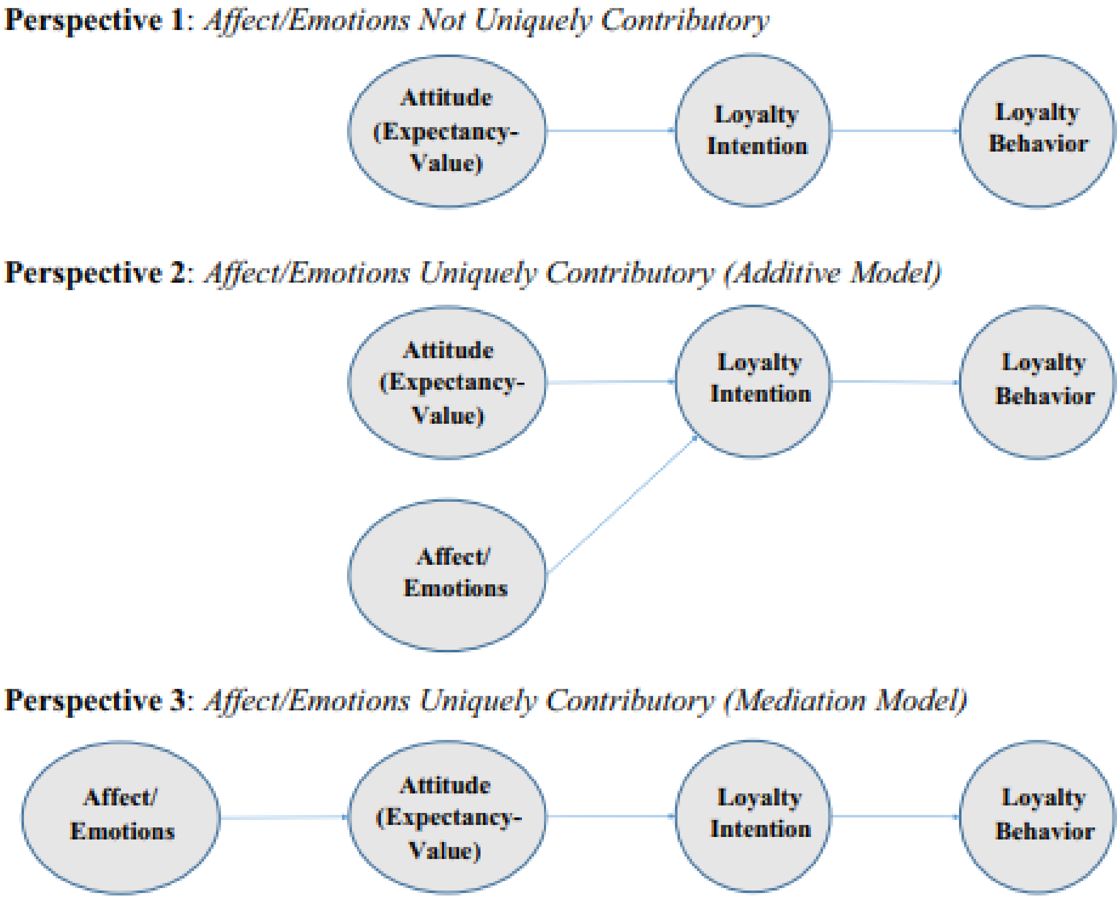


Figure 2-6. Three perspectives for adding affect/emotions to the TRA summarized by Taylor (Taylor et al., 2016)

The first Perspective states that anticipated emotions can only indirectly contribute to intention. The perspective is named by Loewenstein et al. (2001) as the consequentialist perspective that actually characterized many of early behavioral models and the whole field of judgment and decision-making theory development.

The TRA authors stated that affects and emotions “can be considered as background factors that influence beliefs and evaluation . . . and can thus have an indirect effect on intentions and behavior, mediated by theory’s components.” Fishbein and Ajzen (2010, p. 294). In other words, authors have rejected the idea that anticipated emotions can have a direct effect on behavioral intentions and presented empirical evidence in the study from 2013 Ajzen and Sheikh (2013). According to their point of view, emotions affect only through attitudes and/or subjective norms.

The second important consideration (Perspective 2 in figure 2-6) represents another conceptualization of the nature of consumer attitude, called the addictive model. Leone, Perugini, and Bagozzi (2005) have found out that evaluations are functions of anticipated emotions. For example, individuals experience anticipated emotions while asking themselves ”How do I feel about it?” when making a decision. In short, emotions are connected with a particular goal or concern towards a specific stimulus (like an object, product, person, situation). Emotions are differentiated, relatively short-lived intense responses to events, distinct action tendencies, and subjective experiences.

Perspective 2 is also aligned with previously discussed studies from Bagozzi et al. - MGB theory (Perugini & Bagozzi, 2001c), which stated that the most important differentiator of emotions from attitudes in the marketing context is the way emotions arise. To recap the earlier discussion on MGB, tree most important differences are:

1. TRA and TPB focus on action, while AEs on personal goals achievement;
2. Attitude arise through learning, while AEs are more dynamic and entail self-regulation in response to feedback;
3. Attitudes are usually measured with bipolar items, while AEs with unipolar.

Taking that into consideration, Taylor and colleagues agreed that anticipated emotions directly contribute to the predictive validity of TRA (Taylor et al., 2016) (Perspective 2 in figure 2-6)

This addictive perspective is not only one possible conceptualization of adding anticipated emotions to attitude models like TRA. Maybe, attitudes are a mediator (perspective 3 in figure 2-6). The main logic is that anticipated emotions are previous-period measures, while attitudes are from the current period. The role of attitude as a mediator for emotions was discussed also by van den Hooff, Schouten, and Simonovski (2012) arguments The role and this perspective also align with duel-process models from social psychology. In his study, Taylor offers that “Self-reported attitudes can mediate the influence of AEs on consumer loyalty intentions”.

The offers operationalized their considerations in two models (A and B in figure 2-7). These models were introduced in order to compare two ways of consideration of attitudes: unidimensional of multidimensional.

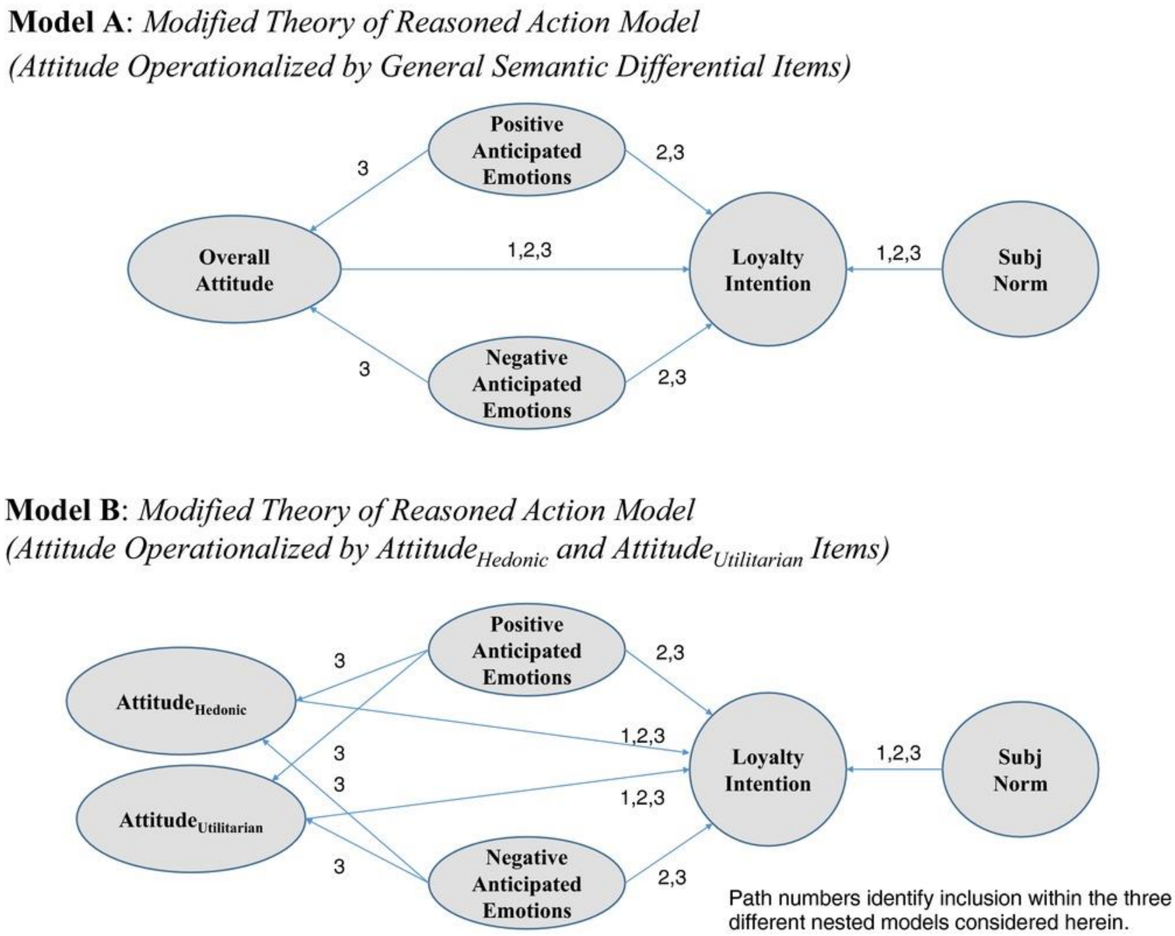


Figure 2-7. Two ways to operationalize attitude and nested models proposed by Taylor (Taylor et al., 2016)

These two models represent two points of view on the attitude: unidimensional or multidimensional with two unique dimensions: hedonic and utilitarian.

In 1991 Batra and Ahtola (Batra and Ahtola 1991) presented empirical evidence supporting the hypothesis that **consumer behavior depends on product attributes** and attitudes are differentially salient across different products. Later, other researchers Voss, Spangenberg, and Grohmann (2003) operationalized this conceptualization, representing two variables for attitudes:

1. *Hedonic Attitude* – the attitude that results from sensations arise from the *experience* of using the product;

2. *Utilitarian Attitude* – the one formed by the *functions* performed by the product.

This perspective to look at the attitude in two dimensions has been widely considered by other researchers in the marketing field perceived shopping value and retail outcomes (Jones, Reynolds, & Arnold, 2006), development of customer relationship (Stathopoulou & Balabanis, 2015), the value of experience (Prebensen & Rosengren, 2016) and others.

It is important to note that the multidimensional perspective does not change basic logic and the underlying assumptions related to the concepts of attitude described with TRA. However, according to the authors, it has the potential to provide greater insights.

Authors have tested the models and their hypothesis using SEM and the results supported the significance of attitudinal variable for predicting consumer behaviors. Moreover, attitudes work better for prediction when they are easy to access (recall) and do not change much over time. Authors, however, pointed out that more research is required to understand the nature of different marketing appeals. Having a better understanding of how attitudes are formed would get much better insights to the managers and help them influence the desired behavior.

Taylor and colleagues not only were attempting to compare behavioral models: TRA, TPB, and MGB, but also deepen the understanding of the relationship between attitudes with anticipated emotions. From this point, this research gave the motivation for this dissertation.

As to the author's opinion regarding “which behavioral model is the best?”

“TRA, TPB, and MGB all have a claim to being the “best model” for consideration of consumer marketers. The answer really depends on the research question driving the marketer’s modeling efforts”(Taylor et al., 2016)

Regarding limitations, the authors noted that the results should not be generalized and more validation in other research settings is needed. In other words, everything related to emotions and behavior is situational and depends on many factors.

In this block, we discussed a few prior attempts to integrate emotional effects into behavioral models n order to improve their predictive power, spotted limitations, and gaps in the current research state. However, before moving to the research question formulation, it is necessary to deepen understanding of the concept of Anticipated Emotions by looking at the prior research in the field.

2.3.3 The four-fold framework

Scientific research related to anticipated emotions went in different directions over the last years. The big branch of research was focused on the effect of specific emotions, with particular attention to the negative ones, such as regret and the impact of it regarding actions and inactions. Several theories postulated that our decisions are guided by the desire to reduce negative feelings that we might be experiencing in the future as a result of decisions taken now. (Hetts, Boninger, Armor, Gleicher, & Nathanson, 2000; Loomes & Sugden, 1982; Patrick et al., 2009a; Zeelenberg, Beattie, Van der Pligt, & de Vries, 1996).

Even if Anticipated Emotions are also often classified by valence as positive or negative, not necessarily positive emotions will motivate purchase decisions, while negative emotions will not. On the contrary, it was found that both categories can either motivate a purchase decision or motivate a non-purchase decision. For example, the anticipation of regret: feeling that by rejecting purchase now, we will regret not doing it in the future, will motivate us to purchase.

Another stream of research is was focusing on this idea. The most influential conceptualization was proposed by Mellers and colleagues (B. Mellers et al., 1999) and is called the framework of decision affect theory. The framework suggests that both negative and positive anticipated emotions are taken into account by individuals during decision-making. In other words, that decisions are functions of subjectively expected pleasure. The framework showed great predictive results in the simulated gambling situations.

This framework was later adopted by other researchers. One of the conceptualizations was proposed by Fong and Wyer: the theory of anticipated emotions in figure 2-8 (Fong & Wyer, 2003). They assumed that the likelihood of making a decision is partly a function of the subjective expected utility of the choice concerning all alternatives. Moreover, they suggest that this subjective utility is not just active units (money, etc.), but can be defined in units of *affect*. According to the abovementioned framework of decision affect theory usually, there are no isomorphic relationships between the objective value of the choice outcome and the subjective feelings attached to it. Moreover, these feelings can depend on how the real outcome compares with those that other individuals have received in similar circumstances.

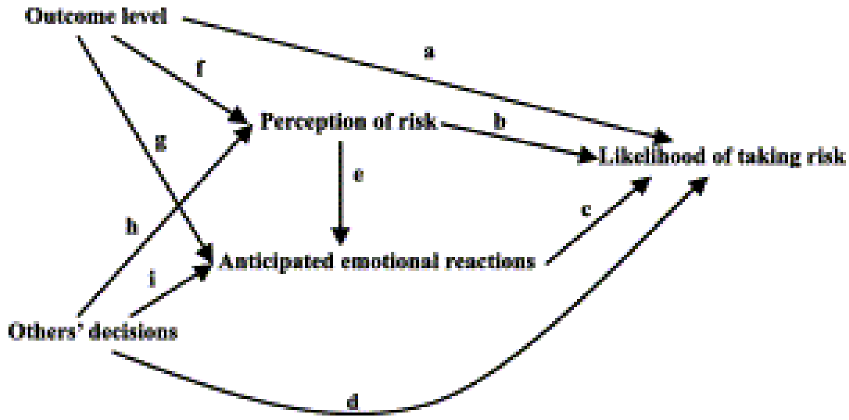


Figure 2-8. The theory of anticipated emotions (Fong & Wyer, 2003)

In short, this theory suggests that people generally aim to avoid negative post-decisional emotions and to gain positive post-decisional emotions.

Considering this perspective, Anticipated emotions can be split into four groups:

- positive AEs toward action;
- negative AEs toward action;
- positive AEs toward inaction;
- negative AEs toward inaction.

This approach will be referred to as *a four-fold framework*.

Another broad direction of research has taken into consideration only some Anticipated Emotions, or, only particular contexts. An example in the economic field – works of Patrick and colleagues considering anticipated emotions in gambling settings, investments (Patrick et al., 2009), without discussing in detail purchase decisions, but more looking at Anticipated emotions in a broader sense.

The perspective of the existence of those 4 types of anticipated emotions has found wide adoption. I other words, it is saying that Anticipated Emotions can cause both positive and negative outcomes regardless of their valence. Consumer anticipate various combinations of emotions (Patrick et al., 2009)

Another evidence in favor of a significant influence of the four kinds of anticipated emotions was found also by Fong and Wyer (Fong & Wyer, 2003). They have conducted two experiments. In the first one participants were given $40,000 and asked to decide on what to do with the money. Options were the following:

1. invest the money in a risky firm with an outcome of either doubling the investment or losing all the money;
2. put money into a time deposit.

The results showed a strong correlation that positive affective expectations had a positive impact on deciding in favor of the first option. On the other hand, negative affective expectations of a failed investment directly impacted negatively the first option. In the second experiment, participants were put in the setting of exam preparation and were asked to decide on the preparation strategy for an important exam. They were offered two options:

1. study only one topic in-depth, which was rumored to be present on the exam – more risky choice;
2. study all the topics, but obtaining a “C”- safe option.

The results revealed that b the first choice generated positive and negative affective expectations that led to positive and negative influences on the decision to take a risky choice. Moreover, the presence of the second option entitled affective expectations for taking a risky choice and produced positive and negative significant influences on taking the risky choice.

Inspired by this study, another group of researchers decided to apply a four-fold framework to the real purchase scenarios (Bagozzi et al., 2016), analyzing deeper the inter-relationship of anticipated emotions on consumer behavior together with other relevant affects, such as persuasion or information processing. Scholars proposed the following framework based on the four-group logic (figure 2-9).

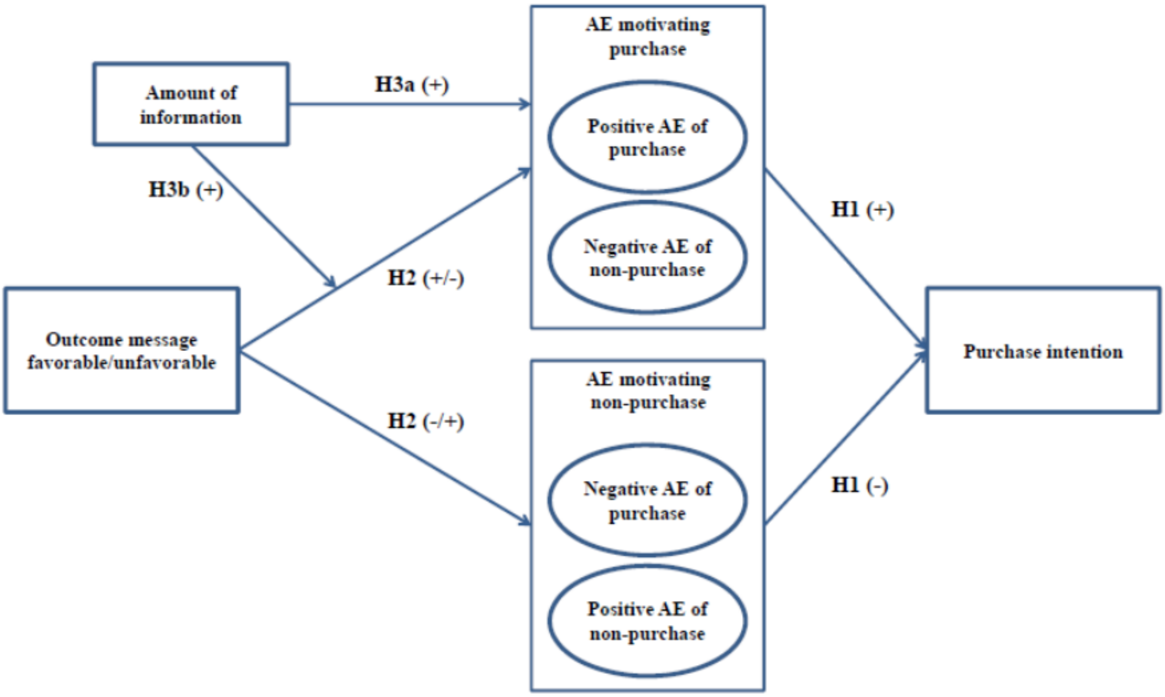


Figure 2-9. Framework and proposed hypotheses: role of AEs in purchase decisions. (Bagozzi et al., 2016)

Their results supported the four-fold framework in the purchasing behavior context. Moreover, their research deepened the understanding of the role of Anticipated emotions by re-interpreting the different theoretical approaches underlying and by investigating anticipated emotions formation in a commercial setting. Moreover, the study revealed the importance of often ignored positive anticipated emotions leading to a non-purchase decision.

Another finding is that anticipated emotions the results herein clearly demonstrate that AEs do not only work independently of each other but also correlate positively with other anticipated emotions that are relevant for the same decision.

Moreover, researchers have found the impact of the amount of information on triggering AEs. Information influences AEs motivating purchase (the higher the amount of information, the higher is the level of AEs). However, it does not influence AEs motivating non-purchase.

The most important finding of the abovementioned studies is that ***anticipated emotions both negative and positive can influence the decision both towards purchasing and non-purchasing***, however, there are some limitations.

The main limitation arises from the fact that ***Anticipated Emotions and the significance of their impact might depend on the context.*** For example, the author assumes that "purchase of frequently purchased products might be instinctive and do not imply the impact of Anticipated Emotions" (Bagozzi et al., 2016) Another case can be spontaneous purchases: do we even have time to anticipate consequences fully when we make a spontaneous decision?

Bagozzi and colleagues suggested for researchers to investigate the influence of anticipated emotions towards low-involvement products more in detail, which was one of the motivations for this dissertation.

2.3.4 Differences in Emotional Responses

Another stream of research on anticipated emotions was investigating more in-depth the difference between emotional responses and their effects on intentions depending on the situation, context, product to be purchased, and the type of decision to be made.

It is clear at this point that Anticipated Emotions are essential for predicting consumer behavior and research went deeper in understanding the exact mechanisms behind Anticipated Emotion's influence. One of the crucial questions that can help us to move forward is: Do we experience the same feelings all the time or they depend on the context? Maybe, some patterns are depending on what type of product our purchase decision is referring to?

2.3.4.1 Hedonic vs Utilitrian

The first clear distinction was made between the hedonic and functional (or utilitarian) nature of products (Hoch and Ha, 1986; Batra and Ahtola, 1991; Kempf and Smith, 1998; Ren and Nickerson, 2019; Yang et al., 2020).

In 1991 Batra and Ahtola (Batra & Ahtola, 1991) presented empirical evidence supporting the hypothesis that **consumer behavior depends on these product attributes** and attitudes are differentially salient across different products. Later, other researchers (Dhar & Wertenbroch, 2000; Voss et al., 2003) created more clear idea on the distinction of these two product categories:

1. *Hedonic products* are fun, exciting, delightful, thrilling, and enjoyable
2. *Utilitarian products* are effective, helpful, functional, necessary, and practical;

Therefore attitudes connected to different product types can be split:

1. *Hedonic Attitude* – the attitude that results from sensations arise from the *experience* of using the product;
2. *Utilitarian Attitude* – the one formed by the *functions* performed by the product.

This perspective to look at the attitude in two dimensions has been widely considered by other researchers in the marketing field perceived shopping value and retail outcomes (Jones et al., 2006), development of customer relationship (Stathopoulou & Balabanis, 2019), the value of experience (Prebensen & Rosengren, 2016) and others.

Hedonic products are usually consumed for affective/sensory fulfillment aim, while functional products are consumed for utilitarian goals (Strahilevitz and Myers, 1998; Kivetz and Simonson, 2002; Witt Huberts et al., 2014; Lu et al., 2016).

Hedonic goods can be associated with excitement, pleasure, and fun (Khan et al.,2004). Typical examples of hedonic products are perfumes or flowers.

Utilitarian goods, on the other hand, are primarily instrumental, consumption is driven by functional aspects and needs, such as detergents, home security systems, personal computers (Holbrook and Hirschman, 1982; Strahilevitz and Myers, 1998; Wertenbroch and Dhar, 2000).

It is widely accepted to think that hedonic products generate higher levels of emotions than functional products. The marketing implications of these are quite diverse: for example, emotional communication is considered to be more effective for hedonic products. However, other scholars have proved that hedonic offer generates greater emotions only for some customer segments (Drolet et al., 2007).

Recent research by Bettiga and colleagues (Bettiga et al., 2020a)was attempting to examine the difference in both continuous and unconscious responses generated by utilitarian and hedonic products. The authors evaluated both self-reported and physiological responses. However, there was no significant difference between the two product types. Furthermore, the results revealed that individuals do not consciously recognize emotions generated by functional products, while incase of hedonic ones they do: the physiological responses were disassociated from the self-reported ones in the case of the functional products and significantly correlated in case of the hedonic products.

The tricky part is that the classification of products for hedonic and functional does not lie in the product itself, but is connected with individual interpretation (Bettiga et al., 2020a). For example, coffee can be interpreted as functional if an individual consumes it because of the need for stimulation. However, if the consumption is driven by sensory enjoyment of coffee taste, the product can be seen as hedonic.

This point may explain why the results of the recent studies in the field have been so controversial. The emotional reaction may depend on the interaction model and situation, which underlies the need for further research in this direction and inspires partially the research questions of this dissertation, that will be formulated in the next chapter.

Overall, even if it was widely accepted to think that hedonic products generate higher levels of emotions than functional products, recent research has shown different results. After all, it is clear that the is a difference present in terms of emotional responses generated by hedonic versus functional products. However, what is exactly the difference and how we can exploit it, remains not fully clear.

2.3.4.2 Experiential vs Material

Another research (Kumar et al., 2014) was trying to deepen the understanding of this difference and made a distinction between experiences and material goods:

- Experiential purchases – "money spent on doing";
- Material purchases – "money spent on having".

The authors started with the simple example: waiting in line. Indeed, when we recall the last time we waited in line to buy something, most probably the experience would depend on what exactly we are waiting for. They proposed that waiting for experiences and anticipating them is more positive than waiting for material goods. Waiting, in general, is not considered a pleasant experience, since people prefer to consume things now rather than later (McClure et al., 2004).

But anticipation, as already explained before, has also many benefits, the experience of savoring. The famous experiment by Lowenstein (Loewenstein, 1987) has shown that people were willing to go towards waiting rather than receiving now when they were asked about an opportunity to kiss their favorite celebrity. They were willing to pay more for the kiss in 3 days rather than a kiss now, which is a clear indication that anticipation may bring pleasure. However, anticipation is usually considered pleasant only speaking about experiences, when the consumption itself is a feeling.

In order to discover that, Kumar and colleagues have conducted a series of studies (Kumar et al., 2014) and the result revealed, that for experience-based purchases anticipation was significantly different: people reported to be more happy, pleased, and excited rather than waiting for a material good. Furthermore, the authors state the anticipation increases the utility of the purchase.

They explain that waiting for experiential purchases is more pleasurable because of the level of abstraction of people's thoughts about an upcoming purchase. For example, when we are considering buying a new PC, we will probably be thinking about some functions, features for more comfortable usage. However, after acquiring a vacation, we may more focus on the overall experience that is waiting for us, on its purpose. When buying a theater ticket we may think about new connections that possibly can be developed with people we are going this, the discussions the play can provoke, etc. More abstract things rather than features and details. These more abstract thoughts may make experiences more significant rather than material purchases.

The main outcome is that experiential purchases due to higher anticipation may be more frequently put on hold, while material goods consumption has more "give it to me now" mindset (Kumar et al., 2014).

Anticipated emotions not only play an important role in consumer behavior but also depend on the type of purchase towards which people have to make a decision.

2.3.4.3 Necessity vs Luxury

Another interesting dimension is to take the perspective on luxury and necessity goods. This distinction is especially popular in the economics domain. Moreover, widely used for marketing.

Luxury items are the ones not necessary to live, but highly desirable within a culture or society. Traditionally, luxury has been associated with exclusivity, status, quality(Atwal & Williams, 2017) A Luxury goods have some synonyms like premium goods, status goods, superior goods, but the term "luxury goods" is the most popular and recognizable expression, the term has also the broadest meaning. **Luxury is defined as "something more than necessary and ordinary",** they are opposed to necessity goods (Bochanczyk-Kupka, 2019, p. 262).

***Necessity items* are defined as something everyone needs, indispensable things**. They are necessary for human existence, such as water, food, clothing. Their consumption is essential to human survival or is needed for maintaining a certain standard of living. (Bochanczyk-Kupka, 2019, p. 260).

Another important consideration that Bochanczyk-Kupka mentioned is that when it comes to necessity goods, buyers are taking into account only the price-quality ratio and price is usually a defining variable for the purchase decision. In other words, it is commonly accepted that regarding purchase decisions **in case of necessity goods only rational variables (like price) are taken into account** and the emotional side is mostly neglected.

On the other hand, in the case of luxury goods, consumer behavior results from multiple motivations, including different emotional effects (Vigneron & Johnson, 2004), among which there are:

- Veblen effect - Conspicuous Perception;
- Snob effect - Uniqueness Perception;
- Bandwagon effect - Social Value Perception.

For example, the Veblen effect states that the increase in price leads to an increase in demand for luxury goods. This phenomenon, like many others, still does not have complete explanations behind it. (Fassnacht & Dahm, 2018) Unlike necessity goods, **for luxury goods,** it is widely accepted to assume that **emotional effects play a crucial role in a purchase decision.**

Reviewing the literature, we can state that research in Emotions rarely touched the necessity goods category, assuming that choices are affected mostly by rational components. On the contrary, there are plenty of studies on emotional mechanisms behind luxury goods perception (Kim et al., 2016; Makkar, 2014) However, researchers have very rarely touched on the concept of prefectural thinking and never focused specifically on Anticipated Emotions.

2.4 Conclusions for the literature review

To conclude, we discussed in this literature review prior research done in the field of consumer behavior with a focus on emotions starting from the 1970s to-80s and had moved towards our goal to understand *how consumers behave and make their decisions*.

The first block of this chapter described the most influential conceptualizations of behavioral formation. Specifically, the Theory of Reasoned Action (TRA) and its extension – Theory of Planned Behavior (TPB). Theories started with the assumption that behavioral intention often leads to behavior: if an individual intends to do something, he or she will probably do it.

The key idea of TRA is that those behavioral intentions are a function of attitudes ("what I personally think about my choice?") and subjective norms ("what other important to me people think about my choice?"). Subjective norms include Injunctive Norms (my sense of what others think I should do) and *Descriptive Norms* (my own beliefs about what others actually do).

This model showed very good predictive abilities in various areas of research but had an important limitation: worked only with volitional behavior. In other words, TRA will not predict those behaviors that we cannot control, or, maybe, are forced to do and predict only the ones we will or will not perform voluntarily.

For example, even the simple consumer decision of whether to start buying more fruits and vegetables is not entirely volitional. In some regions, those products are simply not accessible, or, costly. Maybe, consumer lives together with parents, who do the shopping and control the family diet.

To deal with this issue, the authors of TRA had developed the extension of their model by introducing a new component: Perceived Behavioral Control. This parameter allows us to include some behaviors that are not entirely under volitional control and could not be covered by the TRA. Perceived Behavioral control parameter allows us to enlarge the scope of decisions the model can work with and improve its predictive power.

Even if both TRA and TPB worked well in diverse contexts, something was missing. One of the meta-analyses examined 142 empirical tests of the models and found that the TPB accounted on average for 40% of the variance in intention and 29% of variances in behavior (Armitage & Conner, in press). The TPB appeared to perform not that well in the prediction of behaviors assumed to have a strong irrational component (cf. Godin & Kok, 1996).

Since the moment TPB was published, many researchers have tried to deepen and broaden this model. The most crucial extension was connected to adding an emotional component to these behavioral models. In the last few decades, researchers all over the world started to consider emotions in decision-making.

The second block of this literature review describes the role of emotions in behavior formation, and the path to major discoveries in the field was described.

We had a brief look at the *communicative theory of emotions* (Oatley, 1988) and the *dynamic theory of emotion* episodes by Stein and associates(Stein et al., 1993). Then made a distinction between *Integral* and *Incidental* emotions. Incidental emotions are the ones we carry with us to the decision that has nothing to do with the decision and normally should be irrelevant to present judgments and choices (e.g. on sunny day professor gave students better marks) In opposite to incidental, integral emotions are those caused by the decision itself. Integral emotions as well as incidental have a huge influence on individuals even if the rational cognitive information will suggest alternative choices. For example, some people feel afraid to fly on airplanes and prefer driving instead, while it is acknowledged that rates of death by driving are much higher than the ones by flying (G Gigerenzer, 2004).

Thurtheron, we discussed another important distinction of emotions that was done using the Valence-based approach. The idea is that all emotions can be divided into positive and negative and emotions of the same valence would have similar effects.

This way people that generally have a good mood and emotions would have more optimistic judgments, while people in bad moods on the contrary are pessimistic (Loewenstein & Lerner, 2003).

Even if the valence-based approach served as a solid base for quite some years, it could not provide explanations of many phenomena and did not capture the effect of specific emotions. One of the first influential theories that went beyond valence was *Appraisal-Tendency Framework (ATF)* (Lerner & Keltner, 2000) It showed that emotional effects occur due to changes in (a) content of thought, (b) depth of thought, and (c) content of implicit goals and provided a solid base for predicting the effect of specific emotions on consumer decision-making. The model allows assessing the choices way more complex than the ones based on valence alone. Apprisal Tendency Framework is extremely useful for understanding the role of specific emotions in decision making.

Moreover, in the second block other relevant for this dissertation discoveries were presented and the complete understanding of the current state of knowledge in the field of emotions in behavior formation was developed. Recently, the research community has realized that apart from current emotions, decision-making can also be affected by future-oriented emotions.

The third block of the literature review focuses on the concept of Anticipated Emotions – perceived consequences of future decisions. Reviewing the literature, it became clear that AEs are very relevant for the behavioral formation and can affect it in many ways. In order to capture these effects, researchers started to include Anticipated Emotions in existing behavioral models.

One of the most influential frameworks is the Model of Goal-Directed Behavior (MGB)(Perugini & Bagozzi, 2001c), which was build based on the abovementioned TRA and TPB and included Anticipated Emotions as one of the new model constructs. This model was performing very well in terms of predictive abilities and enlarged the base of theoretical frameworks that researchers can rely on conducting new studies and designing behavioral interventions.

Moreover, third this block included other streams of prior research done in the field of Anticipated Emotions. We had a look at a four-fold framework, which suggested that two types of AEs:

- *Positive Anticipate Emotions (PAE)* – represent positive feelings about the possibility of goal achievement in the future.
  Examples: Happy, Glad, Excited, Satisfied, Delighted, Content
- *Negative Anticipated Emotions (NAE)* – represent negative feelings arising from the impossibility of goal achievement in the future.
  Examples: Disappointed, Sad, Uncomfortable, Anxious, Angry, Frustrated, Nervous, Agitated.

That can be both purchase-motivation and purchase non-motivating.

One of the crucial points is that not always anticipated emotions have the same effect, there are differences in emotional responses since the effect of emotions on behavior formation depends on many contextual factors. For example, between cases of hedonic and functional goods. **The question *"What does the AEs effect on purchase intention depend on?"* does not has a sufficient answer yet.** Some scholars even suggest that there might be cases where AEs do not apply at all: for example, recurrent purchases that have an instinctive nature (Bagozzi et al., 2016).

Throughout the literature review, we have understood the path researchers made over the last 50 years in the field of consumer behavior regarding emotions and highlighted their major conclusions. Moreover, many unanswered questions have been spotted.

This theoretical background analysis now will help us to build solid empirical research.

Chapter 3.

3. RESEARCH QUESTION AND CONCEPTUAL MODEL

In this chapter, the first steps of empirical research will be described. The empirical research of this dissertation was build following the traditional scientific research framework.

In order to develop a strong research question, I will first analyze and highlight the biggest gaps in the literature, so that this dissertation will bring value to the worldwide research in the field of consumer behaviors and produce new insights for managers. After the research question will be developed, I will proceed with building a conceptual model to answer it. Moreover, this chapter will contain the result objectives and proposed hypotheses that will be tested.

3.1 Gaps in the current state of knowledge

As we saw throughout the whole first chapter, the research attempted to explain the role of anticipated emotions together with other affective stimuli on purchase decisions. As a starting point, let's take the fact that the community had accepted that Anticipated Affects are crucial and should be considered in the prediction of consumer behavior. But how exactly should they be considered and are they relevant in all cases?

Despite the increasing effort of researchers to understand the role of anticipated emotions, the majority of the studies are unable to generalize their findings and additional validations always have to be made for every new research setting. Moreover, while some studies have reported medium-large correlations between anticipated emotions and intentions (e.g., Richard et al., 1998), other studies have found a weak correlation (e.g., O'Connor & Armitage, 2003). It is clear that further investigation is needed.

There is a lack of understanding of how exactly AE affects intentions, Moreover, it was shown that the impact of AEs and what we feel also depends dramatically on what we are buying. Some research regarding how the impact of AE depends on purchase item category was done. For example, it was proven that experience-based purchases are affected by anticipated emotions way more than material-based ones (Kumar et al., 2014) However, researchers have never investigated before ***whether the role of anticipated emotion varies depending on the good category: necessity vs luxury.***

It could be possible that for necessity goods AEs might not imply at all since the purchase might be done instinctively. Moreover, essentials (like food or water) for consumers are frequently purchasing products and the role of AEs is questioned. Bagozzi and colleagues raised this question in the recent review:

"The frequent purchases might be instinctive and not imply AEs. In this sense, the research could investigate the role of AEs in frequent or unprompted purchases... " (Bagozzi et al., 2016).

Maybe, there is simply not enough time to experience anticipation effects since we do not think much about this type of decision? Unlikely, for luxury goods the AEs might have totally different impacts, or, even play a key role regarding a purchase decision. Effects of AEs on luxury goods have never been studied in detail as well, from one of the reviews:

"AEs emerge as a broad field of study with many avenues for additional research like luxury purchases" (Bagozzi et al., 2016)

Moreover, the role of Positive AEs and Negative AEs for these two product categories might be completely different. Necessity good purchases might be mostly motivated by negative AEs, by the fear of stop having something we can not imagine our lives without. On the contrary, for luxury goods, positive AEs might have a key role: satisfaction, excitement, and pride consumers will feel by anticipating having luxury items.

Having that in mind, let's proceed with the formulation of the research question and objectives of this dissertation.

3.2 Research question proposal

Analyzing the abovementioned gaps, we can spot a lack of clarity on how the impact of Anticipated Emotions on behavioral variables depends on what the purchase decision is referred to.

With this dissertation, I attempt to make a distinction between luxury and necessity goods in this sense and understand:

- Do AEs apply for necessity goods?
- Do AEs apply for luxury goods?
- If yes, what kind of AEs and through which mechanisms?
- Does the influence of AEs differ depending on whether we are buying luxury or necessity goods?

The goal of this dissertation is **to examine the impact of consumer's positive and negative anticipated emotions on a purchase decision depending on the good category (necessity vs luxury) through self-reported emotions evaluation.**

Having a better understanding of what is the role of AEs regarding purchase decisions towards luxury and necessity goods would not only bring value to academic research worldwide but also get much better insights to the managers and help them influence the desired behavior.

3.3 Conceptual model development

To answer the research question, we should start with an understanding of the mechanism of how anticipated emotions influence purchase decisions in general, leaving aside the part with luxury versus necessity goods distinction. Behavioral models that were discussed in detail in the theoretical block were taken as a starting point. The most influential behavioral models that can provide a basis for answering the research question of this dissertation are:

1. TRA - Theory of Reasoned Action (Fishbein M. & Ajzen I., 1980)

2. TPB – Theory of Planned Behavior ((Ajzen, 1985a, 1991)

3. MGB – Model of Goal-directed Behavior(Perugini & Bagozzi, 2001d)

Relying on the prior research in the consumer behavior field: "TRA, TPB, and MGB all have a claim to being the "best model" for consideration of consumer marketers. The answer depends on the research question driving the marketer's modeling efforts"(Taylor et al., 2016).

In order to keep the focus on Anticipated Emotions, the decision was made to consider only essential constructs, therefore select the TRA model as a base. Moreover, for this research goal, we should focus only on purchase intention formation, without moving further to behavior. Perceived behavioral control parameter – the main difference between TRA and TPB was reasonably excluded since does not has that significant influence in this application domain.

To conclude, from TRA the following logic will be taken:

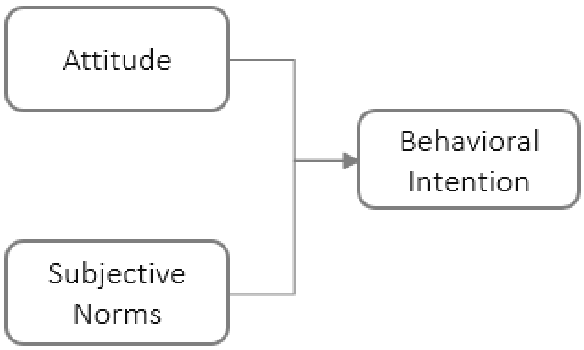


Figure 3-1. Theory of Reasoned Action

The next reasonable question was: how exactly to include emotional variables. We have to consider two possibilities:

1. Direct impact on intention

2. Indirect impact on intention (through the mediation of existing constructs)

Relying on discoveries presented in the last block of the literature review "Integration of AEs to behavioral models", we can conclude that AE can only influence intentions through attitudes and/or subjective norms. The perspective that anticipated emotions can only indirectly contribute to intention is named by Loewenstein et al. (2001) as the consequentialist perspective and is present in many behavioral models and the whole field of judgment and decision-making theory development.

Even the TRA authors themselves stated that affects and emotions "can be considered as background factors that influence beliefs and evaluation and can have an indirect effect on intentions and behavior, only mediated by theory's components." (Fishbein and Ajzen, 2010, p. 294) In other words, they rejected the idea that anticipated emotions can have a direct effect on behavioral intentions and presented empirical evidence in the study from 2013 (Ajzen and Sheikh, 2013). According to their point of view, emotions affect intentions only through attitudes and/or subjective norms.

Taking that into consideration, in this dissertation I propose to use the following conceptualization (figure) as the most reasonable and convenient for the proposed research question and setting:

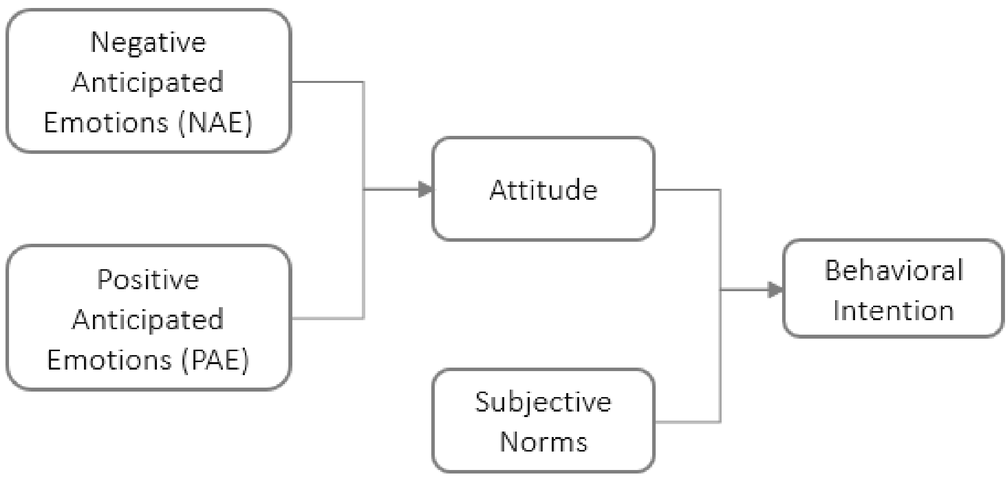


Figure 3-2 Conceptual model.

For anticipated emotional effects, two constructs are introduced:

- NAE – negative anticipated emotions
- PAE – positive anticipated emotions.

Taking a valence-based approach will allow us to better catch the difference between two product categories: necessity and luxury.

Anticipated emotions influence Attitude, which together with subjective norms forms the Behavioral intention. In other words, Anticipated emotions will be considered direct influencers on attitude, and indirect influencers on intention.

3.4 Result objective

Based on prior research, there is evidence that the impact of Anticipated Emotions depends on what do we buy. In this dissertation, I propose that:

H1: *The effect of Anticipated Emotions on Attitude varies depending on good typology: necessity vs luxury.*

Despite the fact, that the emotional effect almost was not considered at all for necessity products since the purchase is assumed to be done instinctively, In this dissertation, I propose that Anticipated emotions do have an impact on attitudes. However, I assume that this affect is mostly covered by NAE, such as the anticipated fear. Individuals might feel worried, uncomfortable, disappointed not being able to reach the goal of buying necessities, which will drive and motivate their purchase intention, thus:

H2: *Negative Anticipated Emotions (NAE) have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.*

On the other hand, I expect that PAE will not be present much among the key decision influencers. It is hard to imagine that individuals will anticipate happiness or excitement before buying bread or water, therefore:

H3: *Positive Anticipated Emotions (PAE) do not have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.*

With luxury goods, the situation is expected to be exactly the opposite: PAE will affect the purchase intention, individuals will savor purchase, anticipate joy and excitements. They may anticipate how proud they would feel about purchasing the luxury item. At the same time, NAE are expected to not have a significant influence., therefore:

H4: *Positive Anticipated Emotions (PAE) have a significant influence on Attitude in the case of Purchase decisions about Luxury goods.*

H5: *Negative Anticipated Emotions (NAE) do not have a significant influence on Attitude in the case of Purchase decisions about Luxury goods.*

To conclude, the general assumption is that Anticipated emotions do impact attitude regarding purchase decisions of both necessity and luxury items, however, that the influence is different: Positive Anticipated Emotions do not have a significant influence on Attitude in the case of Purchase decisions about Necessity goods (H2), while matter a lot in the case of Luxury goods (H3). For Necessity goods, on the contrary, Negative Anticipated Emotions have a significant influence on Attitude in the case of Purchase decisions about Necessity goods (H1), while for Luxury goods they do not matter that much (H4).

Following considerations of the TRA framework, in this dissertation it is also assumed that in both cases Attitude will influence Behavioral intention, so:

H6: *Attitude towards Necessity good influences Purchase Intention.*

H7: *Attitude towards Luxury good influences Purchase Intention.*

Finally, Subjective Norms also have to be considered as the second component in the function of Behavioral formation. It is not that easy to predict, whether the opinion of others will matter for individuals deciding in the proposed context. Moreover, will the influence of subjective norms vary depending on the purchased product category? Based on the prior research presented in the literature review, let's assume that:

***H8:** Subjective norms influence Behavioral Intention regarding the purchase of Necessity goods.*

***H9:** Subjective norms influence Behavioral Intention regarding the purchase of Luxury goods.*

Schematically proposed hypothesis and relations represented at figure 3-3.

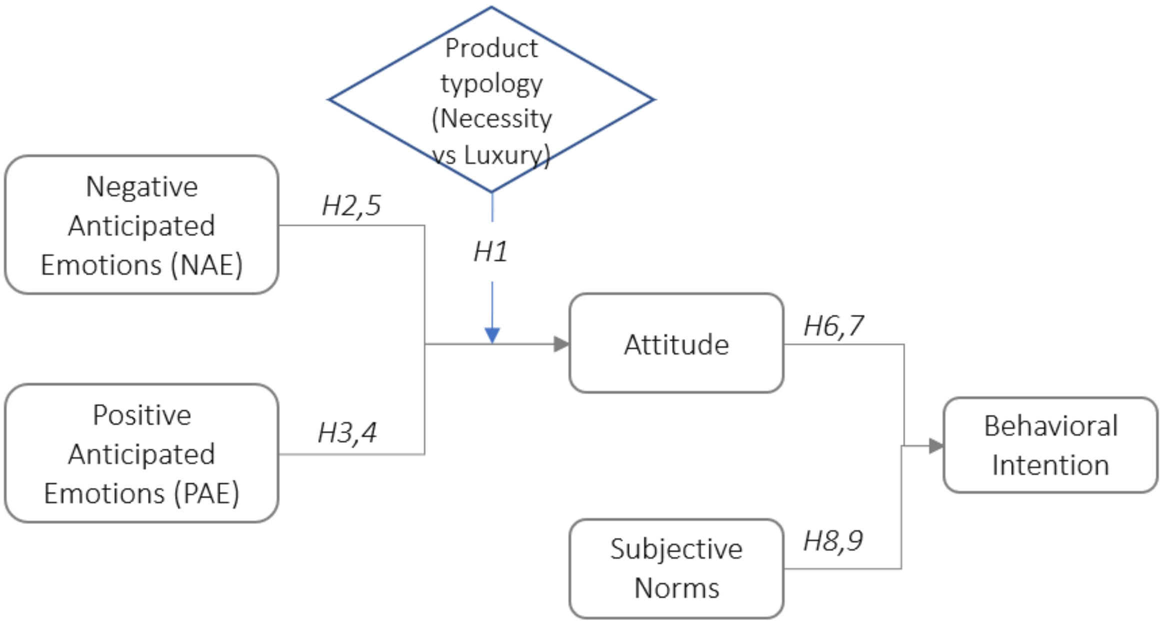


Figure 3-3. Conceptual Model with the proposed hypothesis.

To conclude, it is a TRA-based model with Anticipated Emotions that have an indirect influence on Behavioral Intention through Attitude. As discussed earlier, the effects and relations assumed to be influenced by goods typology (necessity or luxury) towards which a purchase decision has to be made. Therefore, "Product Typology" is introduced as a moderating variable.

The main tool used in the present research work is the survey through which the relationships in the proposed conceptual model are tested and hypotheses are analyzed.

Now, when the research goals are established, we can move towards defining what methodology to adopt to reach this goal.

Chapter 4.

4. METHODOLOGY

This chapter focuses on choosing and describing the methods used to answer the research question, specifically: to examine the impact of consumer's positive and negative anticipated emotions on a purchase decision depending on the good category (necessity vs luxury) through self-reported emotions evaluation. Here the model operationalization will be discussed.

The first block of this chapter describes how the survey to measure self-reported emotions was developed and distributed. In particular, how measures for every construct were developed and what scales were selected. Moreover, clarifying the sample selection and target amount of answers.

The second block will focus on the data processing methodology. How we can analyze the model most efficiently and reliably and check the relationship between constructs? This chapter provides a brief explanation of the selected method PLS-SEM, its advantages, the basic logic behind the algorithm, approach for assessing the Measurement Model and Structural Model. Moreover, statistical parameters that will be used and the meaning behind them will be explained.

The goal of this chapter is to provide readers a full understanding of how the research was conducted and processed.

4.2 Survey development

In this study, the self-reported emotions were measured through the survey, composed of 3 main sections:

- necessity goods
- luxury goods

- demographics

The first two blocks were aiming to access anticipated emotions, attitudes, subjective norms, and intentions regarding purchase decisions toward necessity or luxury goods. It was crucial to let the same individuals provide opinions for both categories, not only one so that I could make better quality results comparison later.

4.2.1 Demographics Section

Section with demographics was introduced to ensure that sample is homogeneous and leave the possibility to analyze correlations with demographic variables in the future in order to figure out not only how Anticipated Emotion effects depend on purchase good category, but also how do they depend on individual characteristics.

Demographic variables included:

- Country of origin;
- Gender;
- Age;
- Occupation;
- Income.

Gender and Age were taken as minimum standard ones, while the others were added due to research specificity. It is accepted to consider that own perception of necessity and luxury goods may depend also on cultural background, social status, income, the desired and accepted standard of living (Bochanczyk-Kupka, 2019)

Even if it is not the focus of this research, further investigation of the influence of the abovementioned variables as moderators could bring even more valuable insights.

All the questions were mandatory. However, to make participants comfortable. To every question in the individual characteristics section, the option “Prefer not to answer” was added.

4.2.2 Main Section: Necessity and Luxury

The other two sections of the survey had identical structures to ensure the reliability of later comparison. They both contain 34 questions that are assigned to measure model constructs.

In the beginning, the definition of necessity good was shown to participants so that they could grasp the basic concept: “A Necessity is a good which is considered essential to a person's well-being”. Then they were asked to think about everyday essentials: rice, bread, drinking water, toilet paper, etc., and pick an example of a necessity item for them (from listed or any other). Also, a visual hint was provided (figure 4.1).

Similarly, for luxury goods. The brief definition in the beginning: “A luxury is a good which increases satisfaction but is not considered essential to well-being.”This was followed by a request to think about luxury items: couture clothing, high-end watches, sports cars, etc., and picking an example of a luxury item that is considered a luxury in your circles and at the same time is realistic, affordable for you.

Figure 4-1. Visual hints were used in the survey in the necessity (a) and luxury (b) goods sections.

Representative examples for both good categories were taken from the book (Bochanczyk-Kupka, 2019) and adjusted for the target sample and the expected majority of the respondents: cultural environment - Europe, social environment - students, young professionals.

Participants were asked to use the item they choose/ keep in mind while responding to the questions (in questions referred to as “necessity item” or "luxury item").

To test the parameters of the conceptual model, the goal was to assign to each construct at least 3 reliable measures, since it is generally recommended by experienced researchers to keep flexibility and possibility of excluding the measure if later it will turn out to be unrelated to construct.

Anticipated Emotions construct

Anticipated Emotions are divided by valance to positive and negative, therefore there are 2 constructs: NAE and PAE. According to the literature review, the most used measures for anticipated emotions in similar contexts were defined by Bagozzi and Peters (Bagozzi et al., 1998) There are 17 emotional terms, introduced in the table 4-1.

Table 4-1. *Measures for Anticipated Emotions.*

Positive Emotions	*Negative Emotions*
Excited	Angry
Delighted	Frustrated
Happy	Guilty
Glad	Ashamed
Satisfied	Sad
Proud	Disappointed
Self-assured	Depressed
	Worried
	Uncomfortable
	Fearful

Based on literature (e.g. Lazarus, 1991; Ortony et al., 1988; Shaver et al., 1987; Watson & Tellegen, 1985) we can notice that for Positive Emotions there are:

- Instances of *positive affect* – Excited and Delighted;
- Instances of *joy* – Happy, Glad, Satisfied;
- Instances of *pride* – Proud and Self-Assured.

For Negative Emotions:

- Instances of *anger* – Angry and Frustrated;
- Instances of *guilt* – Guilty and Ashamed;
- Instances of *sadness* – Sad Disappointed and Depressed;
- Instances of *fear* – Worried, Uncomfortable and Fearful.

Each Emotional indicator should be assigned a numerical number. Relying on prior research works in the area, I decided to use the 7-point Likert scale (unlikely - likely) for each parameter. The numbers were assigned accordingly:

1. very unlikely
2. unlikely
3. somewhat unlikely
4. neither unlikely nor likely
5. somewhat likely
6. likely
7. very likely

By definition, *Positive Anticipate Emotions (PAE)* represent positive feelings about the possibility of goal achievement in the future, therefore the question itself was build in the following way: "If I will manage to successfully buy this necessity/luxury item over the next [period], I will feel..."

Similarly, *Negative Anticipated Emotions (NAE)* represent negative feelings arising from the impossibility of goal achievement in the future, therefore the questions were built like: "If I will not manage to buy this [item] over the next [period], I will feel... (from 1 - unlikely to 7 - likely).

Attitude construct

The next parameter in the conceptual model is Attitude. The approach to measure it was taken from the research paper of Bagozzi and Peters (Perugini & Bagozzi, 2001c) Attitudes were similarly assessed for both necessity and luxury goods. For example, in case of necessity goods: “I think that buying necessity items is...” Then participants responded to 11 sematic items, defined by pairs:

1. Useless ± useful,
2. Ineffective ± effective,
3. Disadvantageous ± advantageous,
4. Stupid ± intelligent,
5. Punishing ± rewarding,
6. Foolish ± wise,
7. Unpleasant ± pleasant,
8. Joyless ± joyful,
9. Boring ± exciting,
10. Unattractive ± attractive,
11. Unenjoyable ± enjoyable.

By assigning value to each item with a 7-point scale. For example, If I think that buying necessities extremely useful, I will put 7. At the same time, I might consider it boring, therefore the value assigned to this pair will be 1.

Subjective Norms construct

The approach to measuring it was taken from the research paper of Bagozzi and Peters (Perugini & Bagozzi, 2001c). Participants were asked to “Think about three most important persons in your life and indicate how much each of them would disapprove or approve you buying [this item] in the next [period]" The numerical value to 3 measures were assigned using 7-point scales anchored by1-disapprove and 7-approved.

Intentions construct

Inspired by the same study, intentions were measured similarly. Three questions were designed (e.g.: "I intend to buy [this item] over the next [period]"). Responses were measured with 7-point scales:

1. completely disagree
2. disagree
3. somewhat disagree
4. neither disagree nor agree
5. somewhat agree
6. agree
7. completely agree

As a result, each construct had 3 measures or more, specifically: NAE – 10 measures, PAE – 7, Attitudes – 11, Subjective Norms – 3, Intentions – 3. Measures are schematically summarized in figure 4-2 and reported with the authors of the approach in table 4-2.

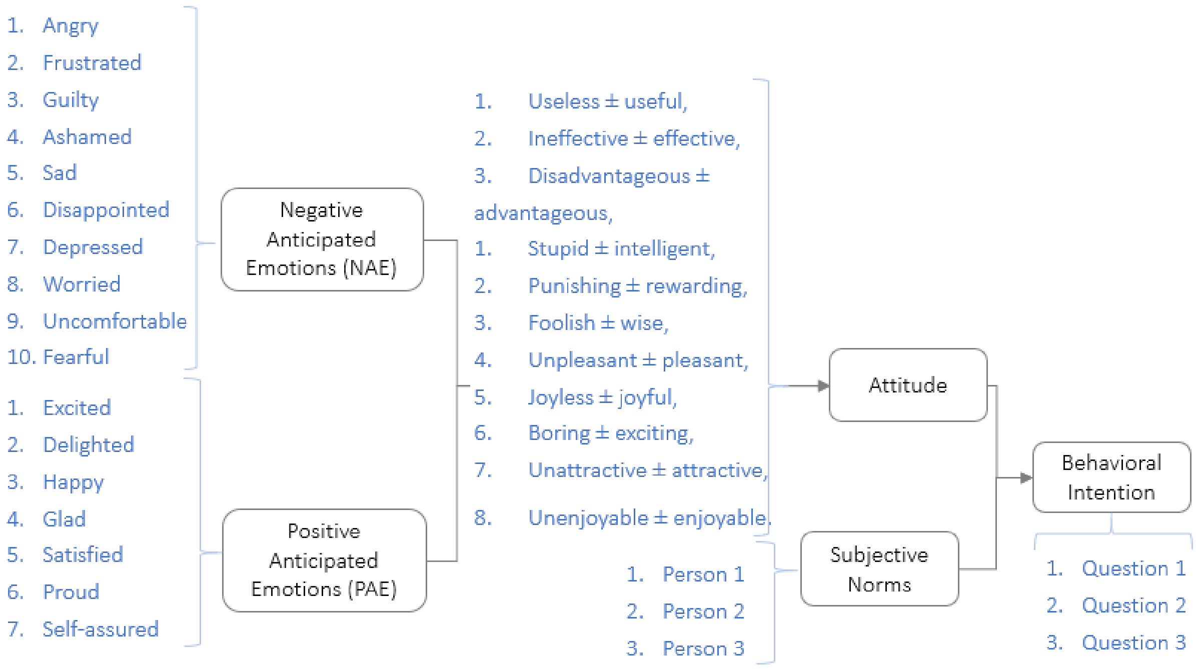


Figure 4-2. The conceptual model with indicators (in blue) used for measuring corresponding constructs.

Table 4-2. *Constructs with corresponding measures and authors of the approaches.*

Parameter	Measures
Positive anticipated emotions (PAE) Bagozzi and Pieters (1998)	If I will manage to successfully buy this [item] over the next [period], I will feel... (from 1 - unlikely to 7 - likely) Excited Delighted Happy Glad Satisfied Proud Self-assured
Negative anticipated emotions (NAE) Bagozzi and Pieters (1998)	If I will NOT manage to buy this necessity item over the next [time period], I will feel... (from 1 - unlikely to 7 - likely) Angry Frustrated Guilty Ashamed

(continued)

	Sad Disappointed Depressed Worried Uncomfortable Fearful
Attitude Perugini and Bagozzi (2001)	"I personally think that buying this necessity item is..." Used 11 semantic differential items on 7-point scales, defined by the pairs: Useless ± useful, Ineffective ± effective, Disadvantageous ± advantageous, Stupid ± intelligent, Punishing ± rewarding, Foolish ± wise, Unpleasant ± pleasant, Joyless ± joyful, Boring ± exciting, Unattractive ± attractive, Unenjoyable ± enjoyable.
Subjective norms Perugini and Bagozzi (2001)	Participants were asked to "Think about the three most important persons for you and indicate how much each of them would disapprove (1) or approve (7) you are buying [this item] over next [period]." A 7-point scale anchored by `disapprove' and `approve' was used.
Intention Perugini and Bagozzi (2001)	I will purchase/ I plan to buy/ I intend to buy [this item] over the next [period]. Used 7-point scale anchored by `unlikely' and `likely"

In total questionnaire consisted of 73 questions, 5 in the demographics section and two sets of 34 in the main section. Despite the big amount, all questions were easy to get and fast to answer, since the scales and question types were unified across the survey. In total, filling the survey was taking around 5 minutes.

4.2.3 Survey validation and distribution

To help avoid biases, at the beginning of the survey quick instruction was given, including the note that there are no correct answers and we are interested in the ones that come immediately to your mind. It was crucial to mention since we are dealing with self-reported emotions.

The scale used from one to seven with a reason to leave participants enough space for expressing emotions with the possibility to answer neutral (by selecting “4”). A 7-point scale helps to solve equidistance problems and obtain sufficient results for statistical analysis.

Once developed, the questionnaire was sent to validation by an internal expert from the Management Engineering School of Politecnico di Milano. After some minor adjustments, the questionnaire was approved.

Furthermore, before the official launch, the survey was tested on a group of students (10 participants) who checked it for clarity and readability, suggested a few minor improvements to the format. After that, a survey was sent to the target sample, which included students and young professionals from Europe.

The surveys were implemented using the google forms tool (forms.google.com) and distributed through:

- Private e-mails to a target sample
- social media platforms (e.g. Facebook, LinkedIn)
- online research forums

An optimal number of responses was calculated according to the following equation:

$$n = \frac{t^2 * p * (1-p)}{m^2}$$

Where

n= Optimal number of responses;

t= Confidence level (90%; z=1.65);

p= Estimated prevalence of the variable under investigation (0.50-0.50);

m= Confidence Interval (10%)

The optimal number of responses is 68. This number was taken as a minimum target. Taking into account the possibility, that not all responses might be correct and complete, the target was set at 150, with the desired number – 200 for better statistical validation of the model. The distribution of the survey started on April 1st and lasted one calendar month, by the end of which the threshold of 200 responses was successfully passed.

Before moving to the data processing stage, collected data was prepared. Furthermore, the reliability of the measurement tool was validated, including Cronbach's alpha and Composite Reliability parameters check. A more detailed description will be given in the next chapter.

4.3 Data Processing method

Once survey results were collected and prepared, data processing is required to find answers to research questions. The main goal of data analysis is to establish relationships between variables in the proposed conceptual model.

Among commonly used simple methods there are univariate and bivariate analysis, correlation analysis. The main problem is that they are limited in the application in terms of handling multiple variables at the same time.

While selecting the method, I also considered Explorative Factor Analysis (EFA) or Confirmative Factor Analysis (CFA). When applied to research, these methods are used to either confirm prior established and tested theories or identify data patterns and relationships. When applied to a data set, the method searches for variables with high correlation and groups them together to reduce a large number of variables to a smaller set of indicators. This final set of factors is the result of exploring the relationship in the date set. So, these techniques have proven to be effective mostly in testing the hypothesis of existing theories.

In the end, the choice was made to make data analysis using SEM (Structural Equation Modeling) – the most suitable for this study technique to establish the relationship between variables. It is a combination of regression analysis with factor analysis, which has proven to be the best technique to test a complex relationship.

4.3.1 PLS-SEM algorithm: basic logic

The algorithm behind the PLS-SEM method was initially developed by Wold (1975, 1982) and later extended and improved by other authors (Lohmöller 1989, Bentler and Huang 2014, Dijkstra and Henseler 2015a).

There are two main types of Structural Equation Modeling (SEM): Partial Least Squares SEM (PLS-SEM) and Covariance-Based SEM (CB-SEM). The second method is usually adopted for confirming already established theories, while PLS-SEM is more convenient to use for exploratory research, where the goal is to find patterns in case there is no sufficient knowledge yet on how the variables are related. Since there were no studies present analyzing the context of frequently instinctively purchased Necessary versus Luxury goods and the role of Anticipated Emotions is not clearly established, the choice was towards PLS-SEM. Moreover, for CB-SEM it is better to use only normally distributed data and circular relationships in the structural model, while PLS-SEM works more efficiently with complex models.

PLS-SEM is based on the Ordinary Least Squares regression technique and focuses on the prediction of a specific set of hypothesized relationships, aiming for maximizing the explained variance in the dependent variables together with minimizing the unexplained variance on the other hand.

The method gives the representation of a path model, where path diagrams are used to display visually the relationships and hypotheses examined (Hair et al., 2016). Variables in PLS-SEM are defined as:

- *Constructs* (latent variables) – complex abstract concepts that can not be directly measured. Can be endogenous, when they are explained in the model, or exogenous when they explain other constructs in the model.

- *Indicators* (measures, items) – are directly measured based on data uploaded and combined together to represent the constructs.

Relation between constructs and related indicators as well as relationships between different constructs are represented with arrows, which are always single-lined in order to represent directional relationships (Hair et al., 2016).

Indicators that define a particular construct should be highly correlated with each other and can be interchangeable (every single indicator can be possibly removed without changing the meaning of construct variables). Relationships between indicators and constructs are called outer loadings.

The PLS-SEM method is composed of two sub-models:

- *Measurement model* (inner model) – represents a relationship between measured/observed variables and latent variables in the model, helping researchers to answer the question: “How well-chosen measures for the variables actually represent the variable itself?”

- *Structural model* (outer model) - represents a relationship between conceptual model’s latent variables, helping to answer the question: “What relationship in the studied conceptual model is stronger and weaker?”

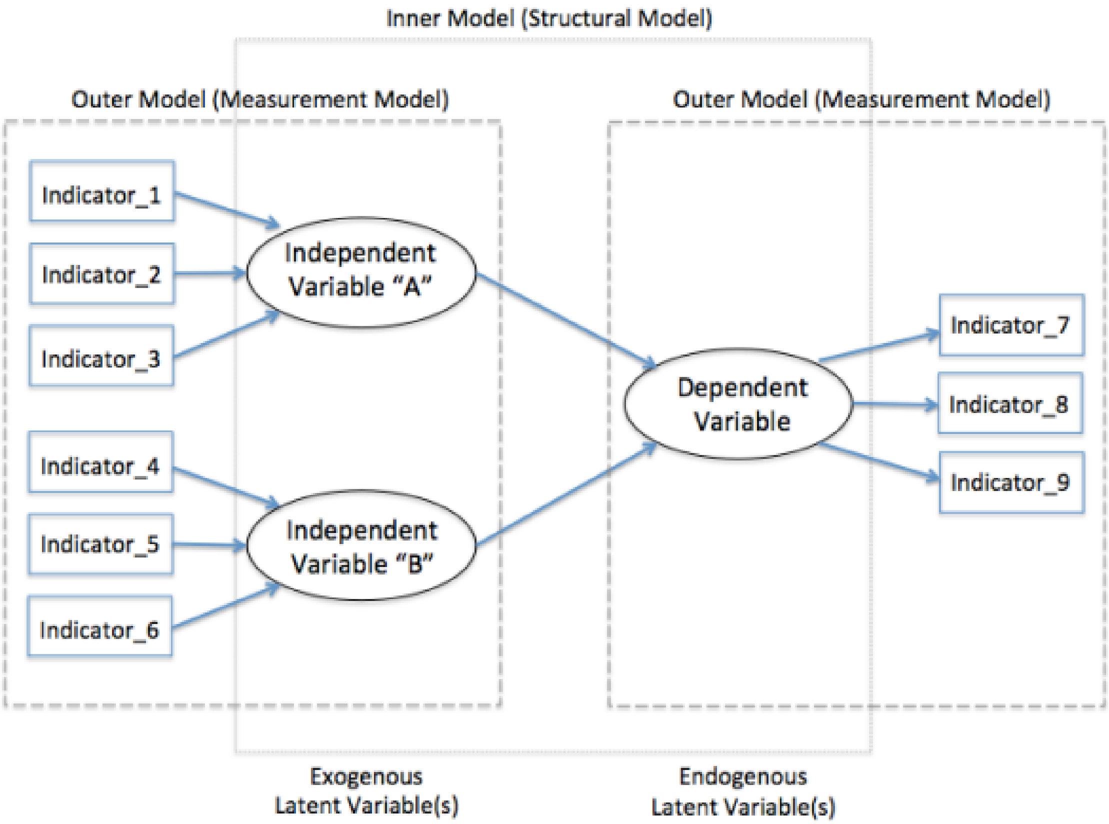


Figure 4-3. PLS-SEM Outer and Inner models (Marketing Bulletin, 2013, 24, Technical Note 1)

The advantage of PLS-SEM is that both the Measurement model and Structural Model can be tested together. PLS is an iterative algorithm that solves the structural equation model by using the measurement and structural model in alternating steps, estimating the latent variable. The measurement model presents the latent variables as a weighted sum of the indications with which they were measured. The structural model uses multiple linear regression between the latent variables already estimated by the measurement model. As a result, providing the relationship between latent variables. This algorithm repeats itself many times until convergence is achieved.

It is important to note that indicators can be reflective or formative depending on the approach to the model assessment. Literature (Hair, Hult, Ringle & Sarstedt, 2016;

Garson, 2016) states that there are two types of approaches to measure unobservable variables:

- *reflective* measurement model;
- *formative* measurement model.

In the case of the reflective model, measures account for manifestations of the corresponding construct, those indicators are seen as a selected sample of all possible available items that might represent construct. Because it is assumed that reflective indicators are caused by the same domain of the construct, indicators connected with this construct must be highly correlated with each other. They also should be interchangeable, meaning that every single construct can theoretically be left out or replaced with another reflective construct of the same domain without affecting badly the construct meaning. In the reflective measurement model, the relationship between latent variable and indicator is called *outer loadings* (Hair et al., 2016).

In the case of the formative model, the main idea is to rely on the assumption that indicators from the construct are obtained by linear combinations and each indicator explains only a specific aspect of the construct. This way, only after bringing all the indicators together, we can obtain a complete meaning of the construct and fully include the nature of the construct. Since each formative indicator adds specific value, they are not interchangeable and it is not recommended to leave out one of them. The relationships between formative indicators and latent variables are called *outer weights* (Hair et al., 2016)

The choice between reflective or measurement models depends on the specificity of the study and the nature of the constructs. In this dissertation, reflective indicators will be used since measures used are complementing each other and may the construct definition more precise, however, excluding some of them will not change the construct's nature.

Important note also how the *minimum sample size* for the PLS-SEM algorithm should be chosen. With time, researchers have developed rules of thumb and theories. There are two most adopted ones. First, developed by Barclay and Smith (Barclay & Smith Jr, 1995) states that the minimum sample size should be 10 times bigger than the number of arrowheads painting at the latent variable at every pace of the PLS path model. The second approach is proposed by Cohen (Cohen, 1992) and suggests that minimum sample size should depend on minimum R2 values identified in any endogenous construct at the structural level.

4.3.2 Approach for Measurement Model Assessment

According to the literature(Hair et al., 2016), the main points to pay attention to during the measurement model assessment are:

- internal consistency reliability;
- convergent validity;
- discriminant validity.

Internal consistency reliability evaluated composite reliability (CR) parameter. Composite reliability (CR) takes into account the outer loadings of each indicator and its measure varies between 0 and 1 values. Higher values indicate higher levels of reliability. Generally, the following ranges are used to evaluate composite (Hair et al., 2016):

• CR < 0.6: lack of reliability;

• 0.61 < CR < 0.70: acceptable for exploratory research;

• 0.71 < CR < 0.90: acceptable for more advanced stages of research;

• CR > 0.95: accepted, but not desirable: outlines that all the indicators are measuring the same phenomenon.

Convergent validity is the extent to which a measure correlates positively with the alternative measures of the same construct. The average variance extracted (AVE) is the most commonly used parameter to evaluate the convergent validity of the constructs c

The average variance extracted (AVE) is calculated as the grand mean value of the squared loadings of the indicators associated with the particular construct. The sum of the squared loadings divided by the number of indicators:

$$VE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

$where$

$\lambda \, represent \; the \; standarlixed \; outer \; loading$

$n \; is \; a \; number \; of \; items$

Outer loadings are values that represent the reliability of individual indicators. Generally, researchers use the threshold of 0.70 to accept an individual indicator (Hair et al., 2016). However, this value is subjective and the most important is to reach desirable AVE. It is not recommended to exclude indicators even with lower loadings in case there are no issues with AVE. As to AVE, its value should be higher than 0.50. This way, the construct explains more than half of the variance of its indicators. A lower than 0.50 value of AVE will indicate that, on average, more variance remains in the error of the items than in the variance explained by the construct (Hair et al., 2016).

Discriminant validity is the extent to which a construct is truly distinct from other constructs by empirical standards. To ensure discriminant validity we need to confirm that a construct is unique and represents phenomena that are not represented by other constructs. Parameters used to evaluate discriminant validity:

- Cross-loadings;
- Fornell-Larcker criterion;
- Heterotrait-monotrait ratio (HTMT) of correlations.

The cross-loadings account for the correlations between an indicator and another construct. Therefore, the outer loading of the indicator should be higher than any of its cross-loading on other constructs.

Fornell and Larcker (1981) suggest that the square root of AVE in each latent variable can be used to establish discriminant validity - Fornell-Larcker criterion. This value should be larger than other correlation values among the latent variables. The logic behind the Fornell- Larcker criterion is that every construct shares more variance with its associated indicators than with any other construct.

However, recent research is stating that neither the FornellLarcker criterion nor cross-loadings can fully ensure discriminant validity. For example, cross-loadings fail to detect a lack of discriminant validity when two constructs are perfectly correlated, and the Fornell-Larcker criterion performs poorly when indicator loadings of the constructs under consideration differ not much (Hair et al., 2016).

Recently the Heterotrait-Monotrait ratio (HTMT) was proposed. It represents the mean of all correlations of indicators across constructs and HTMT is the ratio of between-trait correlations to the within-trait correlations. This approach provides an estimation of the potential true correlation between constructs in case they would be perfectly reliable. When it is close to 1, it indicates a lack of discriminant validity. Commonly accepted threshold is HTMT < 0,85. But since PLS-SEM does not need distributional assumptions, the standard parametric significance of parameter tests cannot be applied to evaluate whether the HTMT statistic significantly differs from 1.

Therefore, researchers have developed a solution – *bootstrapping* procedure to derive the distribution of the HTMT statistic. The bootstrapping algorithm allows extracting random sub-samples from the original dataset using the replacement technique. This technique means that each time when an observation is randomly extracted from the sample, it is returned to the sample before the next observation is drawn.

Each sample bootstrap has the same number of observations as the original dataset has. Bootstrapping algorithm is repeated until a large number (usually around 5000) of random subsamples have been created. The obtained bootstrap distribution is an approximation of the original sampling distribution. Moreover, the bootstrap distribution can be used to estimate statistic parameters. The HTMT statistic is just one of the parameters that can be gained through bootstrapping.

Using the results of HTMT statistics it is possible to define a bootstrap confidence interval. Confidence intervals represent the range within the HTMT population value will fall at a certain level of confidence. If the confidence interval contains “1” we can spot the lack of discriminant validity and when the “1” falls outside the confidence interval range, we can say that constructs are empirically distinct (Hair et al., 2016).

There can be cases when discriminant validity is not reached. Two solutions might be adopted:

The first is to eliminate those items that are too strongly correlated with another construct, or reassign them to those constructs (if logically applicable). It will help to decrease the average HTMT correlations.

The second approach to solve the lack of discriminant validity suggests merging problematic constructs together to create a broader and more general new construct. For both solutions, it is also important to check that the convergent validity of the model is not decreasing (Hair et al., 2016).

4.3.3. Approach for Structural Model Assessment

Once the measures for the reflective measurement model have been checked we can move to the structural model assessment. The structural model shows the significance of the relationship between the constructs and helps to evaluate the proposed hypothesis practice, we will adopt a systematic approach, divided into six different steps (Hair et al., 2016).

Step 1. *Assess collinearity.* To measure the level of collinearity, we should compute one of the following parameters:

- Variance Inflation Factor (VIF)
- Tolerance

The Tolerance is the amount of variance for one indicator that is not explained by the other indicators in the same block. The variance inflation factor (VIF) is basically the reciprocal of the tolerance.

The variance inflation factor (VIF) value above 5 and Tolerance value below 0.20 are considered to be a threshold. In this way the level of collinearity is critical and in this case, researchers are recommended to consider construct elimination. According to guidelines (Hair et al., 2016). It can be done in two ways:

- Construct with the critical level of collinearity can be merged with another construct by adding the measures to a single latent variable.
- Creating construct with a higher-order to treat collinearity problems.

Step 2. *Evaluate structural model path coefficients.* Path coefficients are usually in the interval from -1 to +1. Values can be also smaller or larger than -1 and +1. The closer is the module of a value to 1, the stronger is the relationship between constructs (positive or negative respectively). On the other hand, if values are closer to 0, the relationships are less significant.

The threshold for the significance of the relationship depends on the standard error that can be obtained through bootstrapping. Thanks to bootsrapping process, the empirical p-values and t-values can be computed for all path coefficients of structural model.

The empirical t-value: the relationship is statistically significant at a certain error probability (significance level) if the t-value is larger than some critical value. For example, in the case of one-tailed tests the thresholds are:

- 1.28 (for significance level = 10%),
- 1.65 (for significance level = 5%),
- 2.33 (for significance level = 1%).

In the case of two-tailed tests:

- 1.65 (significance level = 10%),
- 1.96 (significance level = 5%),
- 2.57 (significance level = 1%).

The choice of the type of test and significance level to use depends on the objective of the study (Hair, Hult, Ringle & Sarstedt, 2016). For this case, since the study is exploratory in nature, I will consider a significance level of 10%.

The empirical p-value shows the probability of rejecting a true null hypothesis by error assuming a path coefficient significant when in reality it is not. For this study, the p-value should be smaller than 0.1 in order to consider that the path coefficient is significant at a 10% level (Hair et al., 2016).

Together with analyzing just numbers, it is important to analyze also the relevance of the relationship. There might be cases where the path coefficient is significant but very small. Also, coefficients may be analyzed as relative to one another, so if one number is higher, the effect on the latent variable is bigger. In this study, there are no mediating variables, so this step of the structural analysis is quite straightforward.

Step 3 *Calculation of R2-value* - coefficient of determination. R2 is a square of the correlation between actual and predicted values. The R2 represents the predictive power of the model examined. Value varies from 0 to 1, the higher the value - the higher is the predictive accuracy.

For the marketing field, R2 values of 0,67 0,33 and 0,19 for endogenous latent variables may be respectively described as substantial, moderate, or weak (Chin 1998, p.323)

Step 4 *Calculation of f2-value* – effect size. This value shows the change in R2 value when the exogenous construct is omitted from the structural model. It is the way to evaluate whether omitted construct has a substantive impact or not on the exogenous construct.

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

As a rule of thumb, f2 of 0.02, 0.15, and 0.35 are seen as a gauge for whether a latent variable has a weak, medium, or large effect at the structural level. f2-values lower than 0.02 considered to represent no effect at all.

Step 5 *Calculation of Q2-value* – predictive relevance. Q2 value serves as an indicator of the out-of-sample predictive power of the model. The model with high predictive relevance is able to correctly make predictions even with data not used for the model estimation.

$$Q^2 = 1 - \frac{\sum_D SSE_D}{\sum_D SSO_D}$$

$where\ D - omission\ distance$;

$SSE - sum\ of\ squares\ of\ prediction\ errors$;

$SSO - sum\ of\ squares\ of\ observation$

Q2 values more than 0 indicate that model has predictive relevance, while values below 0 indicate a lack of predictive relevance (Hair et al., 2016). This value is calculated by applying the blindfolding process in smart pls. Blindfolding is an iterative technique that makes sample reuse and omits every data point in the endogenous construct's indicators. As a result, Blindfolding estimates the parameters with the remaining data points.

Step 6 *Calculation of q2-value* – effect size. Similarly to f2, measures the relative impact, but of predictive relevance Q2:

$$q^2 = (Q^2_{included} - Q^2_{excluded})/(1 - Q^2_{included})$$

As a rule of thumb, q2 of 0.02, 0.15, and 0.35 are seen as a gauge for weak, medium, or large effect respectively.

4.3.4 Multigroup analysis (MGA)

After checking the measurement and structural model for both datasets, it is time to figure out whether there are significant differences in group-specific model estimation and to evaluate better the difference between two cases: necessity goods and luxury goods. In this case, the good typology plays the role of moderator.

Moderation effects demonstrate an interaction between exogenous variable (predictor) and endogenous variable (Henseler & Chin, 2010). The example is given in Figure 4-4.

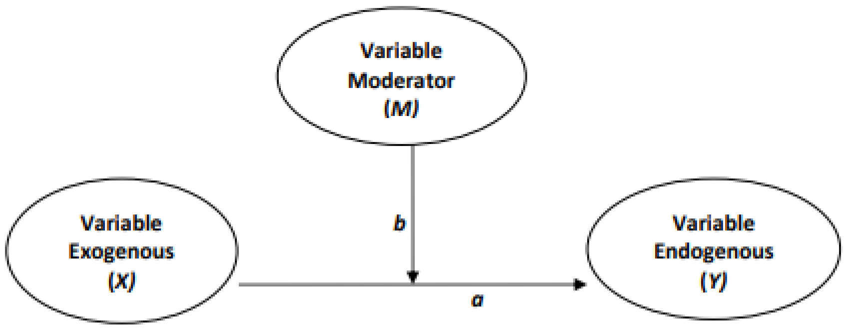


Figure 4-4. Inner interaction model analysis.

In general, for PLS-SEM four approaches can be used to test moderation effects.

- Hybrid approach (Wold, 1982);
- Product indicator approach (Chin et al., 2003);
- Orthogonalizing approach (Little et al., 2006);
- Two-stage approach (Henseler & Chin, 2010).

All approaches have specific application domains and conditions and have to be chosen according to the purpose. For example, the two-stage approach is particularly effective for handling collinearity problems.

However, since in this study product typology is a categorical moderator, the *multi-group analysis* should be applied. It is also called multisampling analysis and is usually carried out to compare two or more sets of data.

In the PLS-SEM algorithm multi-group analysis (or MGA) includes five classifications:

- parametric test;
- permutation test;
- non-parametric test;
- moderating test;
- OTG.

The main differences are in types of data groups. Firstly, the data should be split after estimating the outer model with PL-SEM. Total resamples should be the same for conducting the bootstrapping procedure. Moreover, the variance between groups should be noted and recognized whether the same or not. According to Ringle and colleagues (Ringle et al., 2012) measurement of invariance is reported in three out of six studies. To deal with it, the methodology suggests applying the Smith-Satterthwaite test in the situation when the group's variance is different.

To summarise, the recommendations for reporting the multigroup model are present in table 4-3.

Table 4-3 *Descriptions guidance for the inner multi-group model by* (Latan & Ramli, 2013).

Reporting multigroup model	Recommendation / Rule of Thumb	References
Type of approach	The type of approach for the multi-group model analysis including the software program should be disclosed.	-
Total resamples in the bootstrap	The total resamples for each group of samples in the bootstrap procedure should be the same.	(Chin et al., 2012a; Latan & Ghozali, 2012a)
Invariance measurement	Report the invariance measurement, the Smith-Satterthwaite test is applied if the group is invariant.	(Chin, 2000; Chin et al., 2012a; Latan & Ghozali, 2013)
Total group samples > 2	If the group sample is more than two, the OTG approach can be applied.	(Sarstedt et al., 2011b)

To conclude this brief explanation, PLS-SEM estimates the significance of relationships (structural model path coefficients) and maximizes the R2 values (amount of explained variance) of the (target) endogenous constructs. The algorithm implies two steps: Measurement model analysis and structural model analysis. In the end, the assessment of the path model is concluded. According to the abovementioned characteristics, PLS-SEM serves perfectly the needs of this study and therefore was selected as a data processing method.

4.3.5 Tool for Data Analysis

When it comes to the practical implementation of the PLS-SEM algorithm, there are few available software solutions, such as SmartPLS, XLSTAT's PLSPM package, Adanco, PLS-GUI, WarpPLS. In this research, the most popular (according to Garson, 2016) one has been chosen: SmartPLS 3. Indeed, apart from good technical performance, it has the most user-friendly interface among all other tools. SmartPLS was called the most comprehensive and advanced by gurus in the method (Hair et al., 2016) This software has the biggest diversity of parameters, including the ones necessary to be analyzed for this study.

For the abovementioned reasons, the conceptual model present herein will be analyzed using the PLS-SEM algorithm with SmartPLS 3 graphical interface.

Chapter 5.

5. RESULTS

This chapter presents in detail the PLS-SEM research results. Firstly, descriptive statistics for the demographic section of the questionnaire are reported, including Age, Gender, Nationality, Occupation, and Average Annual Income of the respondents. The descriptive part is followed by PLS-SEM analysis that includes the Measurement and Structural Model analysis. As explained earlier, the measurement model is used to ensure the Reliability and Validity of the constructs. The structural model evaluates the significance of the relationship proposed in the conceptual model (figure 5-1).

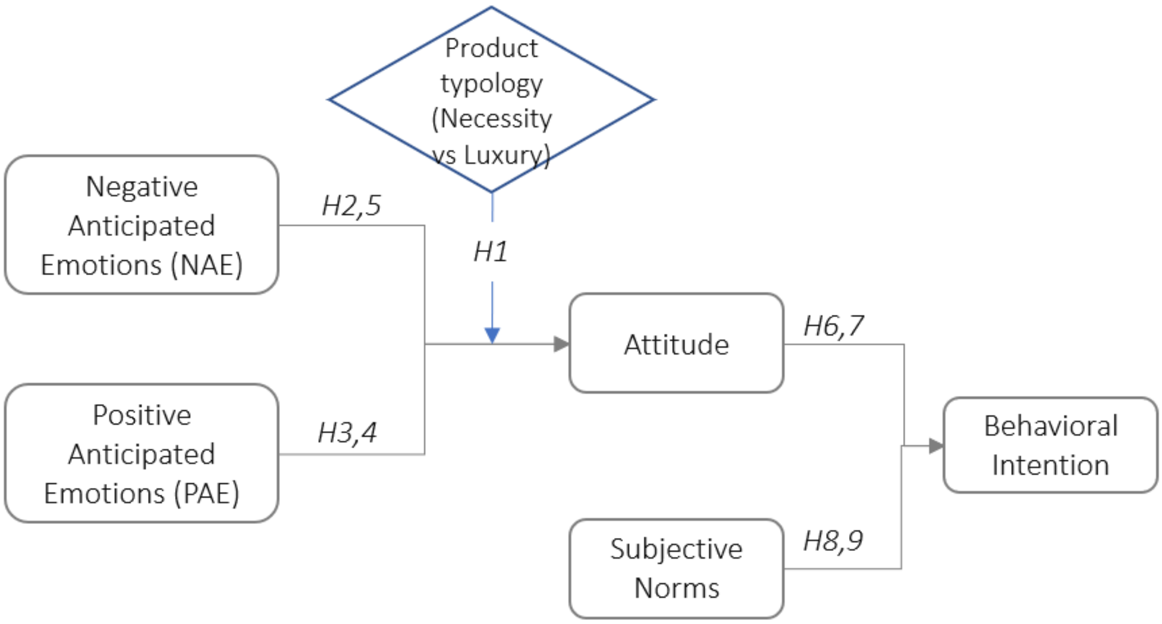


Figure 5-1. Conceptual Model with the marked hypothesis.

The goal of this chapter is to evaluate a hypothesis about inter-relationships that has been proposed for this dissertation:

H1: The effect of Anticipated Emotions on Attitude varies depending on good typology: necessity vs luxury.

H2: Negative Anticipated Emotions (NAE) have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.

H3: Positive Anticipated Emotions (PAE) do not have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.

H4: Positive Anticipated Emotions (PAE) have a significant influence on Attitude in the case of Purchase decisions about Luxury goods.

H5: Negative Anticipated Emotions (NAE) do not have a significant influence on Attitude in the case of Purchase decisions about Luxury goods.

H6: Attitude towards Necessity good influences Purchase Intention

H7: Attitude towards Luxury good influences Purchase Intention

H8: Subjective norms influence Behavioral Intention regarding the purchase of Necessity goods.

H9: Subjective norms influence Behavioral Intention regarding the purchase of Luxury goods.

In order to execute PLS-SEM analysis, the conceptual model was built the SmartPLS software. Each latent variable was assigned a short name: PAE – Positive Anticipated Emotions, NAE - Negative Anticipated Emotions, ATT – Attitude, SN – Subjective Norms, INT – Behavioral Intention. In figure 5-2 the inner model used to define relationships between latent variables is present.

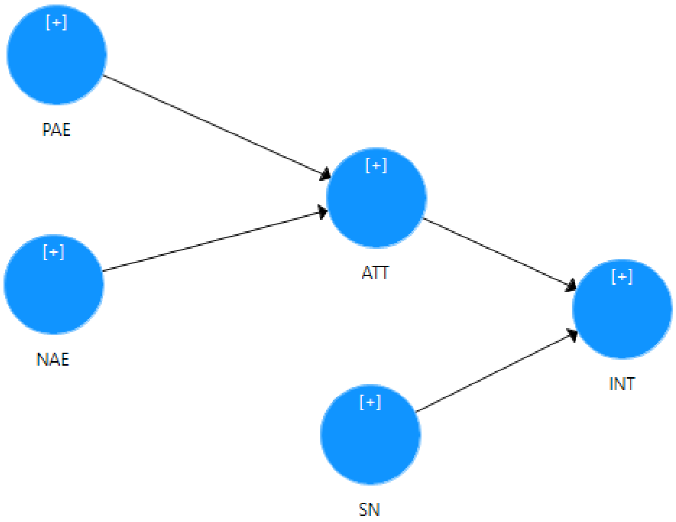


Figure 5-2. SmartPLS model with the latent variables (blue circles) and proposed relationships (one-headed arrows).

Based on the measurement model developed, described detailed in chapter 3, each latent variable was formed by at least 3 reflective indicators (figure 4-3). Each indicator variable was given a short name. For Subjective Norms and Intentions, there were 3 questions designed for each (with indicators short names SN_1 SN_2, SN_3, and INT_1, INT_2, INT_3 accordingly), while for other indicators meaning is the following:

- PAE_1 Angry
- PAE_2 Frustrated
- PAE_3 Guilty
- PAE_4 Ashamed
- PAE_5 Sad
- PAE_6 Disappointed
- PAE_7 Depressed
- PAE_8 Worried
- PAE_9 Uncomfortable
- PAE_10 Fearful

- NAE_1 Excited
- NAE_2 Delighted
- NAE_3 Happy
- NAE_4 Glad
- NAE_5 Satisfied
- NAE_6 Proud
- NAE_7 Self-assured

- ATTITUDE_1 Useless ± useful,
- ATTITUDE_2 Ineffective ± effective,
- ATTITUDE_3 Disadvantageous ± advantageous,
- ATTITUDE_4 Stupid ± intelligent,
- ATTITUDE_5 Punishing ± rewarding,
- ATTITUDE_6 Foolish ± wise,
- ATTITUDE_7 Unpleasant ± pleasant,
- ATTITUDE_8 Joyless ± joyful,
- ATTITUDE_9 Boring ± exciting,
- ATTITUDE_10 Unattractive ± attractive,
- ATTITUDE_11 Unenjoyable ± enjoyable.

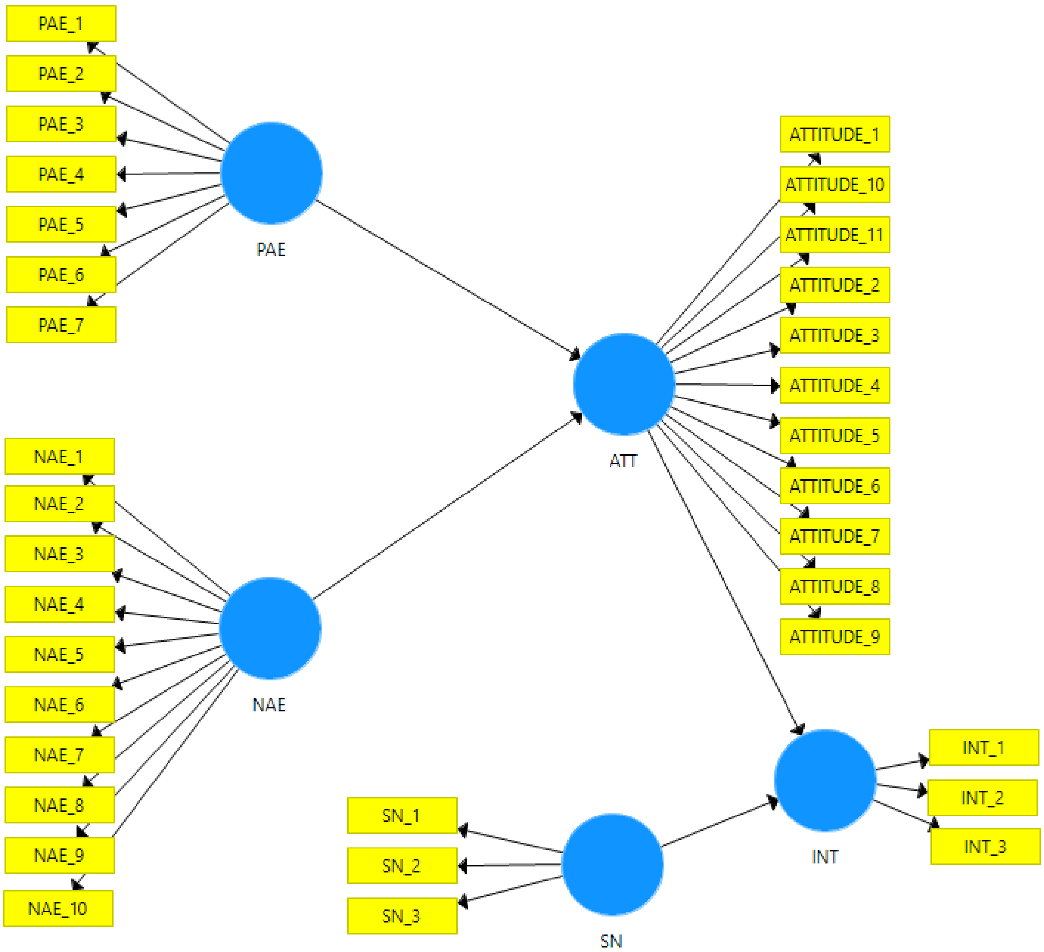


Figure 5-3. The conceptual model in SmartPLS.

5.1. Demographic Profile of the respondents

In the present study, respondents were asked to share information about their characteristics. Each question was mandatory, but to make respondents feel more comfortable, the option: “Prefer not to say” was added to each question. In particular, the survey included questions regarding:

1. Age
2. Gender
3. Country of origin
4. Occupation
5. Average Annual Income

Age Group

The majority of respondents (87,7%) are Young Adults and belong to the Age group 18-34, of which 48,3% are in the group of 25-34 and 39.4% in the group 18-24. The group with the least number of respondents is 55+ (1%). Table 5-1 and figure 5-4 show the distribution of respondents by age group.

Table 5-1. *Respondents Distribution by Age Group*

Age Group	Frequency	Percentage
18-24	80	39,4
25-34	98	48,3
35-44	5	2,5
45-54	17	8,4
55+	3	1,5
“Prefer not to say”	0	0
Total	203	100

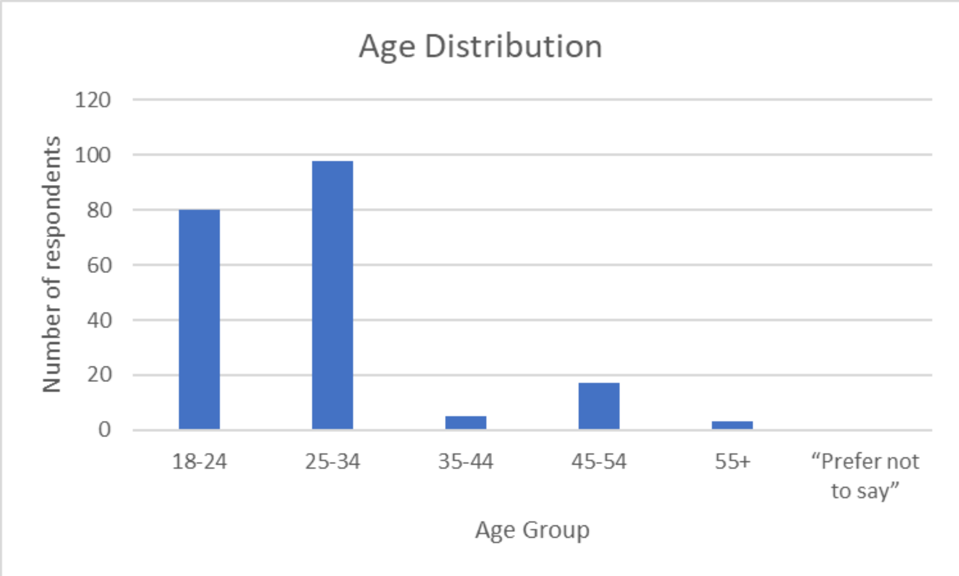


Figure 5-4. Respondents Distribution by Age Group

Gender

The respondents were quite balanced in terms of gender. However, female respondents were present a bit more frequently (57,6%). The Distribution by gender is present in Table 5-2 and Figure 5-5.

Table 5-2. *Respondents Distribution by Gender.*

Gender	Frequency	Percentage
Female	117	57,6
Male	83	40,9
“Prefer not to say”	3	1,5
Total	203	100

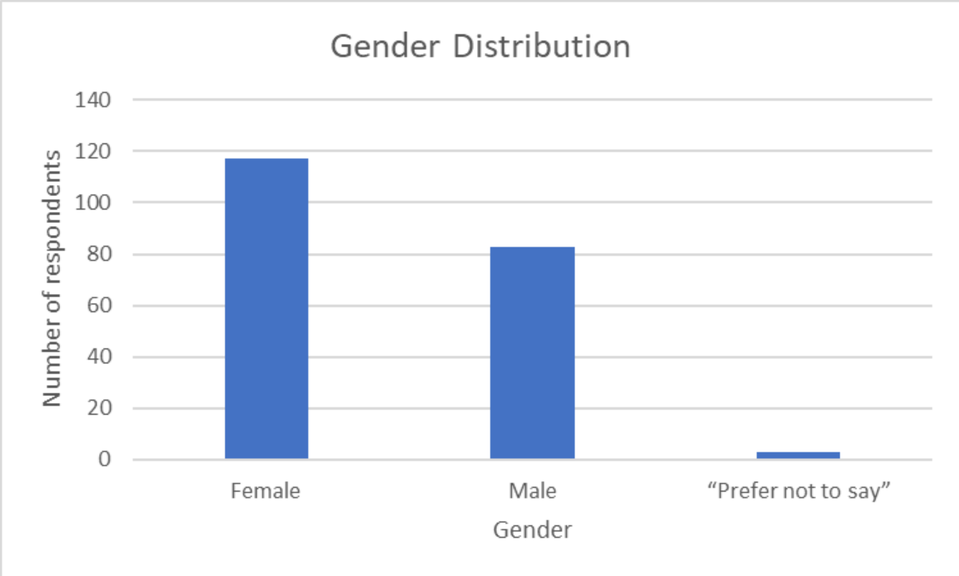


Figure 5-5. Respondents Distribution by Gender.

Country of origin

Respondents were asked to identify their country of origin. The frequency distribution for answers shows that the majority of respondents are from Italy (40,9%), Russia (19,2%), and Romania (13,8). The rest were from other EU – countries, with only 2,9% of replies outside of Europe. The Distribution by country is present in Table 5-3 and Figure 5-6.

Table 5-3. *Respondents Distribution by Conty of Origin.*

Natinality	Frequency	Percentage
Italiy	83	40,9
Russia	39	19,2
Romania	28	13,8
Other EU contries	47	23,1
Other non-EU countries	6	2,9
“Prefer not to say”	0	0
Total	203	100

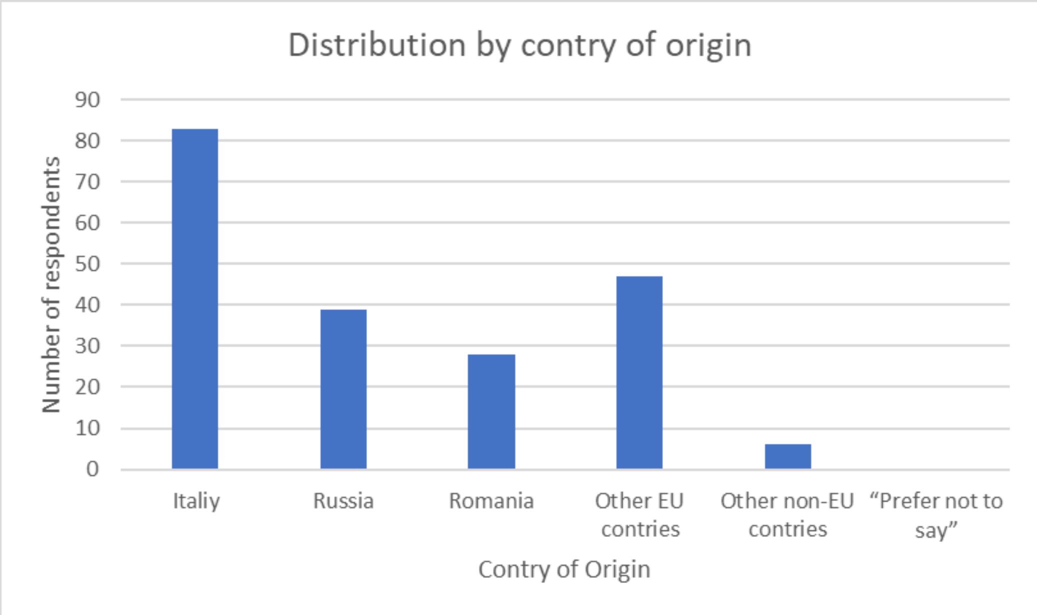


Figure 5-6. Respondents Distribution by Country of Origin.

Occupation

Subjects in the study also identified their occupation. The majority of respondents are young professionals – employed (48,3%), or, students (32,5%), The least present group are “retired” – only 2 respondents (<1%). he Distribution by country is present in Table 5-4 and Figure 5-7.

Table 5-4. *Respondents Distribution by Occupation.*

Occupation	Frequency	Percentage
Employed	98	48,3
Self-employed	17	8,4
A homemaker	5	2,5
A student	66	32,5
Retired	2	1
other	15	7,4
Total	203	100

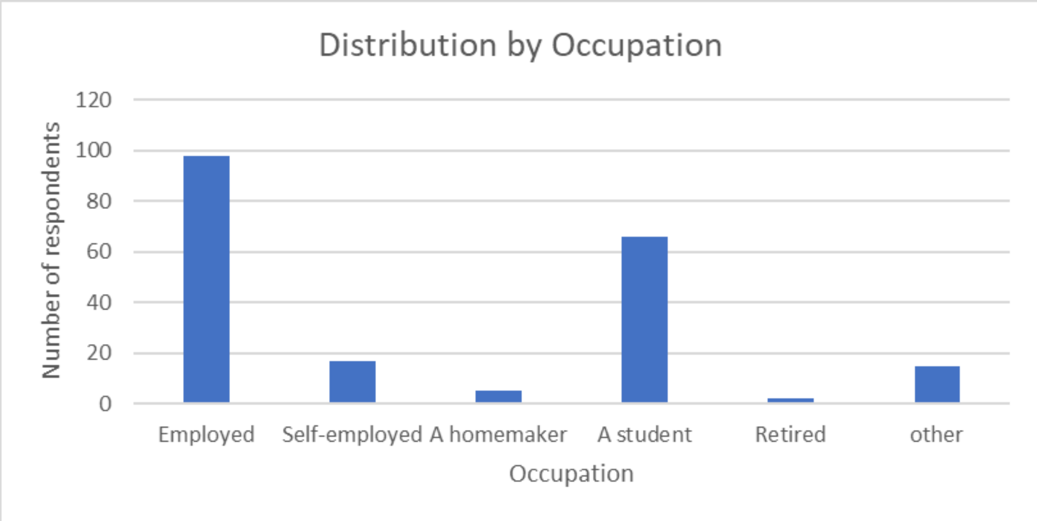


Figure 5-7. Respondents Distribution by Occupation.

Annual Income

Respondents were asked to share their income. Table 4-5 and figure 4-8 show the distribution of respondents by Annual Income. The majority of respondents have an income of €25 000 to 49 999 per year (35%), very few belong to the group €50 000+. The majority are students and young professionals, so the income expectedly matches the occupation distribution.

Table 5-5. *Respondents Distribution by Annual Income.*

Income	Frequency	Percentage
€0	9	4,4
€1 to 9 999	61	30
€10 000 to 24 999	46	22,7
€25 000 to 49 999	71	35
€50 000 to 74 999	6	3
€75 000 to 99 999	3	1,5
€100 000 and greater	0	0
“Prefer not to say”	7	3,4
Total	203	100

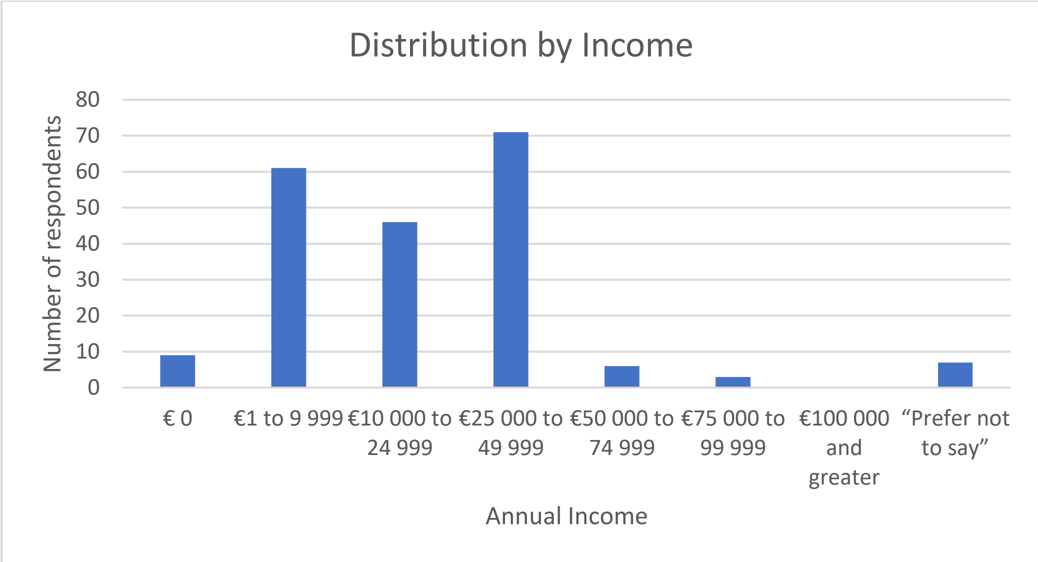


Figure 5-8. Respondents Distribution by Annual Income.

Before reporting the results of PLS-SEM analysis, few preliminary steps are required: questionnaire validation and minimum sample size requirements check.

5.2. Reliability check of the questionnaire

Reliability should be checked to understand whether questions were adequate. In fact, all questions were formulated based on existing studies and were pre-tested (detailed description in chapter 3). Anyway, since the research setup and context are slightly different, the reliability check will be performed.

Reliability check includes evaluation of internal consistency for all scales adopted. As explained earlier, each construct is measured through at least 3 questions, in total 32 scales for each good typology. To check the internal consistency of scales, it is recommended to use Cronbach’s alpha (Bakker, Deremouti& Verbeke, 2004).

The methodology suggests first to calculate Cronbach’s Alpha for every scale and in case some values will be below 0,7, try to recombine the questions by choosing the ones with the highest coefficients (Hair et al., 2016). When Cronbach’s alpha values are higher than 0,7 – questionnaire can be considered reliable. Cronbach’s Alpha of all scales was calculated (Figure 5-9).(Hair et al., 2016). When Cronbach’s alpha values are higher than 0,7 – questionnaire can be considered reliable. Cronbach's Alpha of all scales was calculated (Figure 5-9).

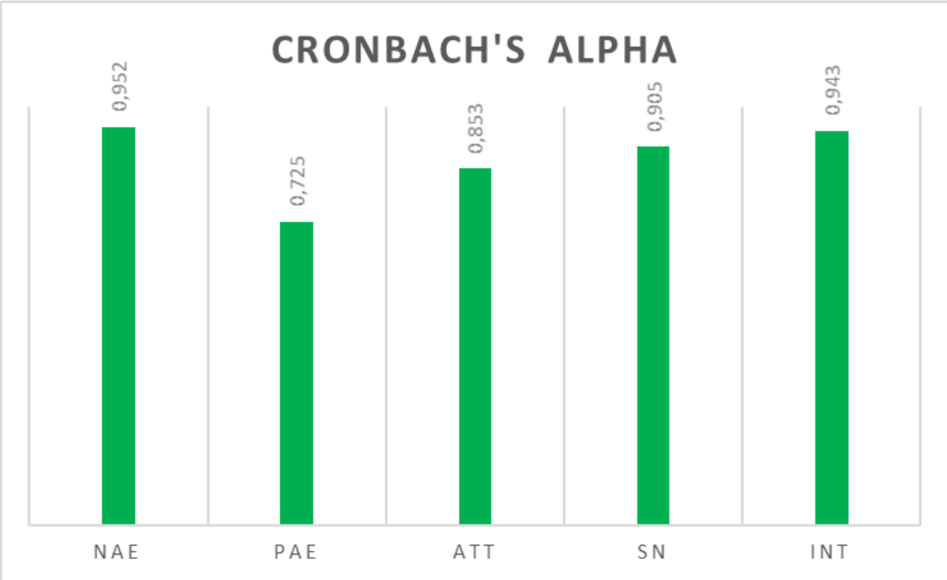


Figure 5-9. Cronbach's Alpha of scales.

As a result, all 5 values showed values higher than 0,7, which means good internal consistency within each scale. Since the questions taken at first place were already tested by other researchers in different research settings, they are reliable and numbers confirmed that. That means that consequently, we can start validation considering all questions of the survey.

5.3. StartPLS 3 software set-up

5.3.1. Partial Least Squares

Before we run calculations, the algorithm requires some basic *setup*. As discussed, the logic is based on a sequence of regressions in terms of weight vectors. Those vectors obtained at convergence satisfy fixed point equations.

Basic settings:

- *Weighting Scheme:* Centroid, Factor, or Path. Path setting provides the highest R^2 value for endogenous latent variables. This scheme is generally applicable for all kinds of PLS path model specifications and estimations, therefore, were selected.

- *Maximum interactions:* This parameter represents the maximum number of iterations that will be used for calculating the PLS results. This number should be sufficiently large (e.g., 300 iterations). Smart PLS suggests when checking the PLS-SEM result to make sure that the algorithm did not stop because the maximum number of iterations was reached but due to the stop criterion. As several interactions 300 were taken by default.

- *Stop Criterion:* The PLS algorithm stops when the change in the outer weights between two consecutive iterations is smaller than this stop criterion value (or the maximum number of iterations is reached). This value should be sufficiently small (e.g., 10^-5 or 10^-7).

Advanced Settings:

- *Initial Outer Weights:* When running the PLS algorithm, the initial outer weights of all indicators in the PLS path model according to initial authors (authors Hair et al. (2017) are set to +1 (this is also the default SmartPLS setting). Alternatively, SmartPLS allows the user to configure individual initial outer weights for every indicator, but in my case was not necessary. For example, a particularly important or dominant indicator may obtain an initial outer weight of +1 (i.e., when assuming a positive relationship between this indicator and its latent variable), while the other indicators of the same measurement model obtain a re-configured initial outer weight of 0. The measurement model in this study is going to be studied from internal consistency, divergent validity, convergent validity perspectives.

- *Computer Memory*: There is also possible to set SmartPLS memory usage, the default 516 MB of the computing device's memory was selected.

5.3.2. Bootstrapping

Basic settings:

- *Subsamples.* In bootstrapping, subsamples are created with observations randomly drawn with replacement from the original set of data. To ensure the stability of results, the number of subsamples should be large. For the preparation of the final result, it is recommended to use use a large number of bootstrap subsamples, therefore we will use 5000 for all bootstrap runs.

- *Parallel processing*. It is possible to choose the option of running bootstrapping on multiple processors to reduce the computation time. This option will be marked in basic settings.

- *Basic vs Complete Bootstrapping*. There are two options available depending on the results detalization needed. The basic set includes only Path Coefficients, Indirect Effects, Total Effects, Outer Loadings, and Outer Weights. The computation time is lower, but it is recommended to use only for preliminary analysis. In case of complete bootstrapping the results will include also R Square, Average Variance Extracted (AVE), Heterotrait-Monotrait Ratio (HTMT), Composite Reliability, and Cronbach's Alpha. Complete bootstrapping uses a Bollen-Stine type bootstrapping for the goodness-of-fit measures. The second option will be used.

Advanced settings:

- *Confidence Interval Method.* It is used for estimating nonparametric confidence intervals and it is possible to choose between: (1) Percentile Bootstrap, (2) Studentized Bootstrap, and (3) Bias-Corrected and Accelerated (BCa) Bootstrap. In this research will be used "Bias-Corrected and Accelerated (BCa) Bootstrap" since it is the most stable method that does not need excessive computing time.

- *Test type:* two-tailed significance test will be used.

- *The significance level* will be 0.05 for confidence interval computations.

5.4. Descriptive statistics

As mentioned earlier, 203 complete answers for each product typology were left for data analysis. In Annex 1 some descriptive statistics are reported separately for both product typologies to leave the possibility of drawing additional conclusions from mean values for each indicator of Anticipated Emotions (PAE and NAE).

The first column presents the range that was similar for all from 1 to 7, then mean, median and standard deviations are shown.

The means (μ), medians, and standard deviations (σ) values for indicators are measured according to the results of the validated questions of the respective indicator.

It is interesting to observe already how different emotions were more anticipated a lot more or a lot less than others. For example, in the case of Necessity goods, even if people were not feeling much excited or, proud (PAE_1 and PAE_6), we see much higher means for PAE_5 (satisfied) and PAE_7 (self-assured). Among all AEs the highest mean value has NAE_9 (uncomfortable), which means that in case of not-purchasing necessity goods people are expected to feel uncomfortable. Moreover, we already can see that Negative Anticipated Emotions were generally higher than positive in the case of Necessity goods.

For Luxury goods, the picture shifted: we can observe that positive anticipated emotions are present to a very high extent (all mean values of PAE_1 to PAE_7 are closer to 7). At the same time, respondents did not anticipate much the negative emotions (all values are closer to 1), only NAE_5 and NAE_6 (both with mean = 2,8) can be noticed.

Those indicators were “sad” and “disappointed”. In other words, not purchasing the product may make individuals sad and disappointed, but to a low extent. Respondents expected much more to feel Excited, Delighted, Happy, Glad, and Satisfied (PAE_1 to PAE_5 all had a mean above 6).

These are some early observations and in order to go deeper in the analysis, we should proceed with PLS-SEM, analyzing not just stand-alone emotions, but their effect on attitudes and other relationships within the conceptual model.

5.5. Measurement model analysis

To understand whether all indicator variables, in reality, reliably represent constructs, measurement model analysis was performed. The goal is to ensure the reliability and validity of the constructs. Reliability represents the consistency, basically clarifying: "If this study was to be conducted at another time with the same subjects and conditions, will the results will be the same? Validity in statistical terms shows weather the constructs measured what it was intended to measure.

My approach for reporting results of measurement model analysis was developed based on literature analysis that is described in detail in the methodology chapter. The summary is present in the figure:

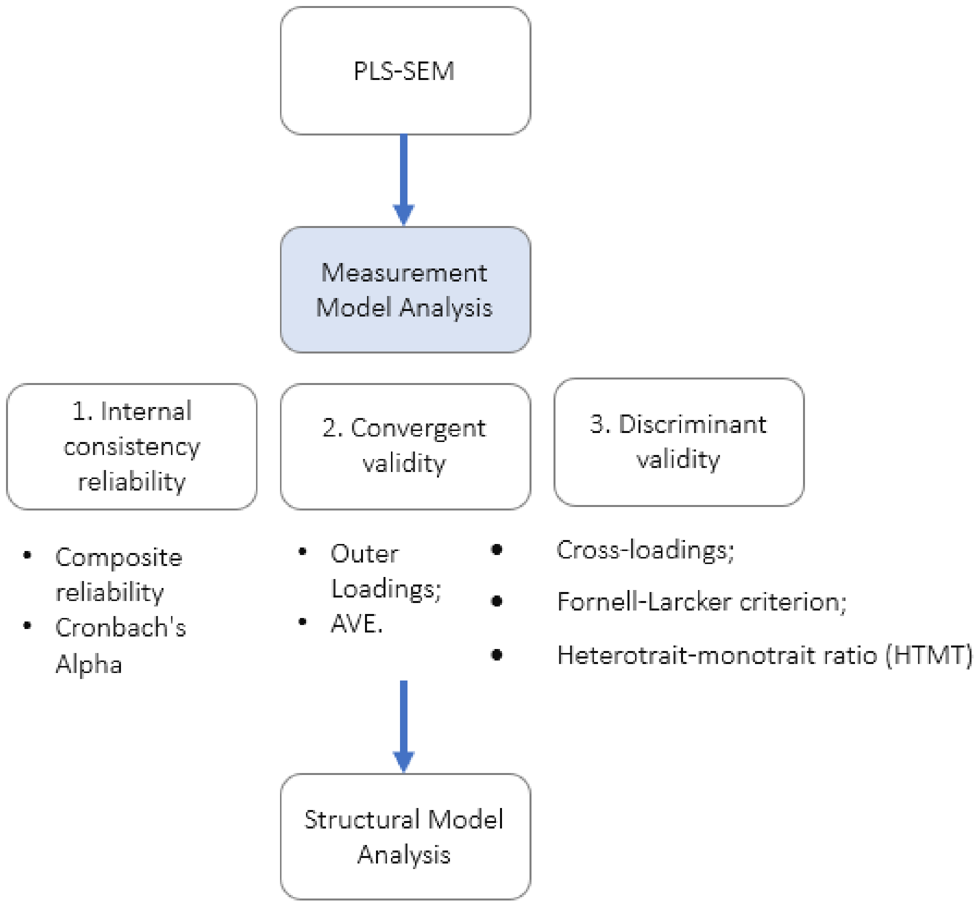


Figure 5-10. Summary for the approach adopted for Measurement model analysis.

5.5.1. Internal consistency reliability

The reliability of variables was tested through Composite Reliability and Cronbach's Alpha. As explained in the previous chapter, the threshold used is 0.70 for both parameters. The results for two data sets: necessity and Luxury goods will be reported separately to leave the possibility of obtaining better insights. Results for necessity goods are reported in Table 5-6 to show Cronbach’s alpha and composite reliability.

Table 5-6. *Cronbach's Alpha and Composite Reliability for the constructs for Necessity goods.*

	Cronbach's Alpha	Composite Reliability
ATT_N	**0.907**	**0.922**
INT_N	**0.950**	**0.942**
NAE_N	**0.924**	**0.937**
PAE_N	**0.873**	**0.846**
SN_N	**0.978**	**0.985**

Results for luxury goods are reported in Table 5-7 to show Cronbach’s alpha and Composite reliability.

Table 5-7. *Cronbach's Alpha and Composite Reliability for the Luxury case constructs.*

	Cronbach's Alpha	Composite Reliability
ATT_L	**0.923**	**0.933**
INT_L	**0.965**	**0.970**
NAE_L	**0.950**	**0.895**
PAE_L	**0.915**	**0.934**
SN_L	**0.764**	**0.864**

Since all values of Cronbach's Alpha and Composite Reliability are a lot greater than 0.70 - commonly accepted threshold (Hair et al., 2016), we can ensure the construct's reliability. (Hair et al., 2016), we can ensure the construct's reliability.

5.5.2. Convergent Validity

To assess Convergent Validity, the Average variance Extracted (AVE) parameter was used:

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

$where$

$\lambda\, represent\ the\ standarlixed\ outer\ loading$

$n\ is\ a\ number\ of\ items$

The recommended threshold, as explained in the previous chapter is 0.05. Before checking AVE, it is important to have a look at Loadings which are at the core of AVE calculation.

Outer Loadings indicate the extent to which each item correlates with the given construct. Loadings can range from -1.0 to +1.0, where the higher the value is – the higher the correlation. The results for Outer loadings are reported in Annex 2.

During measurement model analysis it is recommended to remove variable indicators with very low loadings (<0.50) (Gefen & Straub, 2005).(Gefen & Straub, 2005).(Gefen & Straub, 2005).(Gefen & Straub, 2005).

For Luxury goods parameters, there was one indicator for the Negative Anticipated Emotions (LUX_NAE_10) that had outer loading lower than 0.50 (0,452) and badly affected the overall reliability of the model, there was a decision made to exclude it from measures. The indicator is: "Fearful". Excluding it is adequate, because there are other two measures (NAE_8 "worried" and NAE_9 "uncomfortable" which are as well are instances of fear. The other 9 measures for Negative Anticipated Emotions are sufficient and enough to form the NAE latent variable.

Looking at the Outer Loadings for Necessity-case constructs, excluding NAE_N_10 as well for the overall model consistency, one problem was spotted. We can notice that the PAE_N_5 parameter has a low value (0,376) and therefore has been excluded from Positive Anticipated Emotions construct for both cases of Necessity and Luxury goods. After the exclusion, Cronbach's Alpha and Composite Reliability were double-checked and reached sufficient numbers.

The recommended threshold for AVE, as explained in the previous chapter is 0.50. The values of Average variance Extracted (AVE) are present in table 5-8 and 5-9.

Table 5-8. *Average variance Extracted (AVE) values for necessity goods constructs.*

Construct	AVE
ATT_N	0.520
INTENTION_N	0.986
NAE_N	0.624
PAE_N	0.529
SN_N	0.957

Table 5-9. *Average variance Extracted (AVE) values for luxury goods constructs.*

Construct	AVE
ATT_L	0.559
INTENTION_L	0.971
NAE_L	0.505
PAE_L	0.666
SN_L	0.680

Since all the values are above the threshold, we can confidently say that Convergent Validity has been achieved.

5.5.3. Discriminant validity

Firstly, Cross-loadings were evaluated and analyzed. Results are reported in Annex 3 for luxury goods and necessity goods datasets. For each construct, the outer loadings of the indicators were higher than any of its cross-loadings on other constructs (highlighted with green in the tables in the Annex). In other words, each indicator showed high loading with the construct it was supposed to be assigned to.

The second parameter was the Fornell-Larcker criterion, results are present in table 5-10 and table 5-11 for two goods categories.

Table 5-10. *Fornell-Larcker criterion results for Necessity goods.*

	ATT_N	INT_N	NAE_N	PAE_N	SN_N
ATT_N	**0.721**				
INT_N	0.311	**0.993**			
NAE_N	0.578	0.222	**0.790**		
PAE_N	0.219	0.009	0.225	**0.728**	
SN_N	0.505	0.365	0.287	0.033	**0.979**

We can see that the overall square roots for all constructs are higher than correlations with other latent variables in the conceptual model. This is indicating that every construct is a valid measure of a unique theoretical concept. The same analysis was done for Luxury goods (table 5-13).

Table 5-11. *Fornell-Larcker criterion results for Luxury goods.*

	ATT_L	INT_L	NAE_L	PAE_L	SN_L
ATT_L	**0.748**				
INT_L	0.328	**0.986**			
NAE_L	0.290	0.482	**0.711**		
PAE_L	0.323	0.264	0.278	**0.816**	
SN_L	0.529	0.258	0.122	0.191	**0.824**

The third parameter to be checked is the Heterotriat-Monotriat ratio (HTMT). The results for two good categories are present in table 5-12.

Table 5-12. *Heterotriat-Monotriat ratio (HTMT) results for Necessity goods.*

	ATT_N	INT_N	NAE_N	PAE_N	SN_N
ATT_N					
INT_N	0.321				
NAE_N	0.623	0.235			
PAE_N	0.397	0.169	0.214		
SN_N	0.527	0.368	0.307	0.214	

Since there are no numbers very close to 1, the HTMT results are good. The same check was performed for Luxury goods (table 5-13) and no issues were found.

Table 5-13. *Heterotriat-Monotriat ratio (HTMT) results for Luxury goods.*

	ATT_L	INT_L	NAE_L	PAE_L	SN_L
ATT_L					
INT_L	0.316				
NAE_L	0.235	0.429			
PAE_L	0.372	0.282	0.293		
SN_L	0.624	0.296	0.083	0.235	

The evaluation of the abovementioned criteria is sufficient to ensure discriminant validity (Mura, Lettieri, Radaelli & Spiller, 2014).

To conclude the measurement model analysis, after evaluating internal consistency, convergent validity, and discriminant validity, we can say that model is valid and reliable.

5.6. Structural analysis

Now we are sure that the measurement model (outer model) is properly executed, there is time to assess the structural model (or inner model) and start receiving answers for the research questions posed in this study. The methodology that is detailed described in the previous chapter will be adopted.

Step 1. *Assess collinearity* - To ensure the collinearity of the Inner model, the VIF parameter should be lower than 5. Results are present in tables 5-14 and 5-15.

Table 5-14. *The variance inflation factor (VIF) values for necessity goods constructs.*

Construct	VIF
ATT_L	1.389
NAE_L	1.083
PAE_L	1.083
SN_L	1.389

Table 5-15. *The variance inflation factor (VIF) values for luxury goods constructs.*

Construct	VIF
ATT_N	1.343
NAE_N	1.053
PAE_N	1.053
SN_N	1.343

Since all the numbers are lower than the threshold – 5, collinearity is ensured.

Step 2. *Evaluate structural model path coefficients.* Path coefficients will be first rewired separately of the case of necessity and luxury goods and later on compared using multi-group analysis.

The study of the relationships of the constructs is divided into two steps: firstly, path coefficients are qualitatively evaluated; second, bootstrap analysis is performed to assess the statistical analysis of the relationships.

Necessity goods

Path coefficients (β) obtained through the PLS-SEM algorithm for the case of the necessary are shown in table 5-16.

Table 5-16. *Path coefficients (β) Necessity goods.*

	Attitude	Intention
Attitude		**0.170**
Intention		
Negative Anticipated Emotions	**0.557**	
Positive Anticipated Emotions	**0.094**	
Subjective norms		**0.279**

We can already see the hypothesis of this dissertation is confirming, in case of necessity goods Anticipated emotions do have a significant influence on attitude, however, only negative ones (β = 0,557). Attitude and Subjective Norms together form Intention. The final conclusions will be made after bootstrapping.

Visual representation of the research model is shown in Figure 5-11. Latent variables are shown as blue circles and composed of indicators in yellow. Arrows from latent variables to indicators have the value of respective outer loadings marked on them. Inside the circles of the endogenous latent variables, there are R2 coefficients, which are going to be examined in the next step of structural model evaluation.

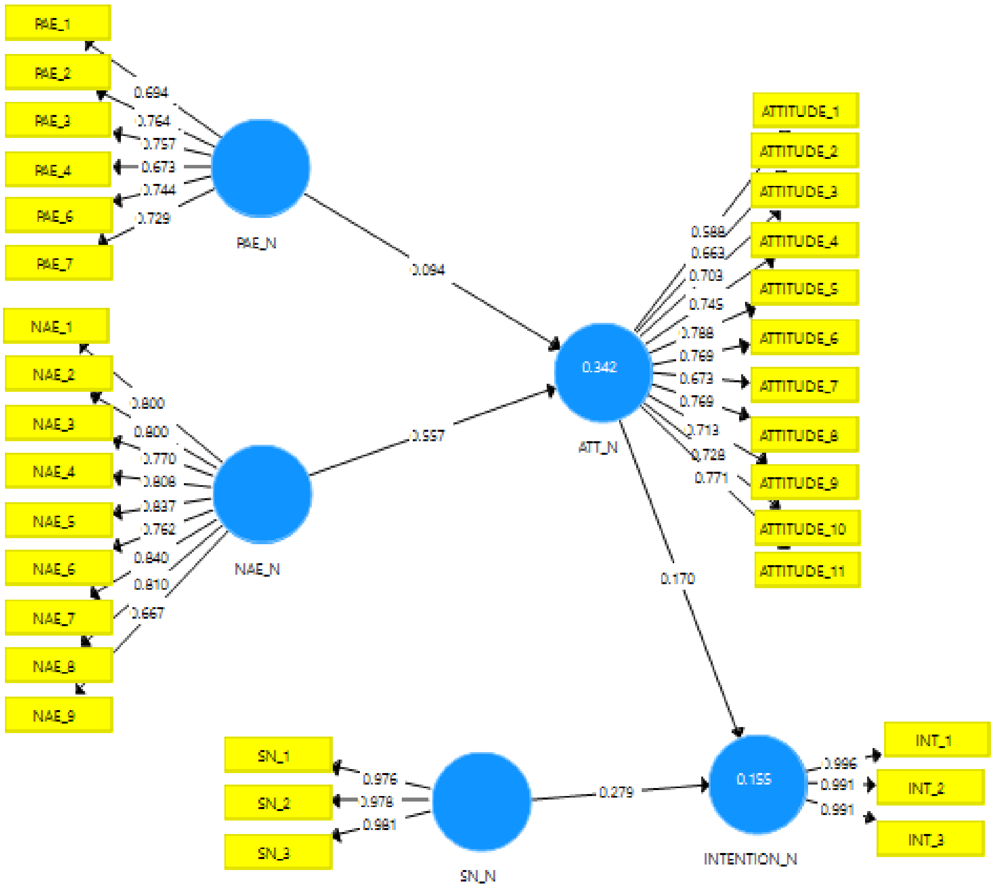


Figure 5-11. Conceptual Model with path coefficients (Necessity goods case).

Luxury goods

Path coefficients (β) obtained through the PLS-SEM algorithm for the case of luxury are shown in table 5-17.

Table 5-17. *Path coefficients (β) Luxury goods.*

	Attitude	Intention
Attitude		**0.265**
Intention		
Negative Anticipated Emotions	**0.217**	
Positive Anticipated Emotions	**0.263**	
Subjective norms		**0.118**

With luxury goods, the situation is slightly different. Anticipated emotions do have a significant influence on attitude, however, positive to a higher extent. Attitude has a significant influence on Intention. Surprisingly, in the case of Luxury goods, Subjective Norms (the opinion of others) do not has a significant influence on the Intention to purchase or not the product. In any case, final conclusions will be done after performing bootstrapping.

Figure 5-12 shows the visual representation of PLS-SEM results for the Luxury goods dataset.

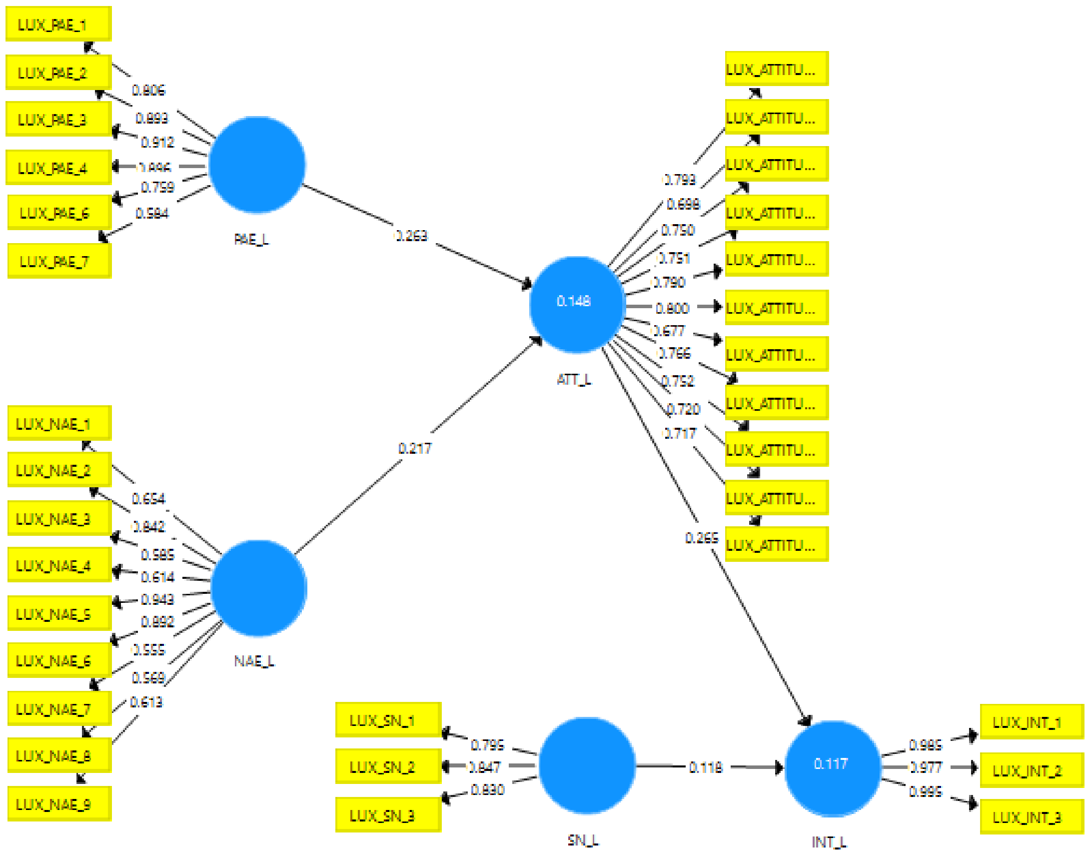


Figure 5-12. Conceptual Model with path coefficients (Luxury goods case).

5.6.1. Bootstrapping

As a part of path coefficients analysis to assess statistical significance a bootstrap re-sampling was performed since PLS does not require assumptions on the distribution of variables observed.

The same basic and advanced settings in SmartPLS software were used for bootstrapping. For evaluating statistical significance, p-values and t-values will be used.

The results of bootstrapping including statistical values are reported in table 5-18.

Table 5-18. *Results of a bootstrapping for Necessity goods case.*

	Original Sample (O)	Sample Mean (μ)	Standard Deviation (σ)	T-Statistics (|O/σ |)	P-Values
ATT_N -> INT_N	0.170	0.175	0.087	1.957	0.050
NAE_N -> ATT_N	0.557	0.556	0.057	9.687	0.000
PAE_N -> ATT_N	0.094	0.130	0.079	1.185	0.236
SN_N -> INT_N	0.279	0.280	0.074	3.775	0.000

As mentioned in the previous chapter, the threshold for the significance of the relationship depends on p-values and t-values can be computed for all path coefficients of the structural model. As explained earlier, t-values should more than 1.28, while p-values lower than 0.1. Looking at the numbers, we can make conclusions on the hypothesis:

- Negative Anticipated Emotions (NAE) have a significant influence on Attitude in the case of Purchase decisions about Necessity goods: 9,687 t-value is much higher than the threshold, therefore **H2 is accepted.**
- Positive Anticipated Emotions (PAE) do not have a significant influence on Attitude in the case of Purchase decisions about Necessity goods: 1,185 t-value is lower than the threshold, therefore **H3 is accepted.**

- H5: Attitude does affect Intention in the case of Purchase decisions regarding Necessity goods since the t-value is 1.957 – above a threshold. This way **H6 is accepted.**

- H7: Subjective norms have a significant influence on Intention (t-value = 3,775), therefore **H8 is accepted.**

Luxury goods

Table 5-19 shows the path coefficients for the Luxury goods case: mean, standard deviation, t-values, and p-values can be found obtained after running bootstrapping

Table 5-19. *Results of a bootstrapping for Luxury goods case.*

	Original Sample (O)	Sample Mean (μ)	Standard Deviation (σ)	T-Statistics (|O/σ |)	P-Values
ATT_L -> INT_L	0.265	0.223	0.130	2.059	0.040
NAE_L -> ATT_L	0.217	0.038	0.284	0.757	0.449
PAE_L -> ATT_L	0.263	0.334	0.105	2.540	0.011
SN_L -> INT_L	0.118	0.150	0.093	1.277	0.202

The situation is much different from the Necessity goods dataset analysis. Taking into consideration the threshold for t-values 1.28, we can make conclusions on the hypothesis:

- Positive Anticipated Emotions (PAE) do have a significant influence on Attitude in the case of Purchase decisions about Luxury goods: 2,540 t-value is higher than the threshold, therefore **H4 is accepted.**

- Negative Anticipated Emotions (NAE) do not have a significant influence on Attitude in the case of Purchase decisions about Luxury goods: 0,757 t-value is low to be considered significant, therefore **H5 is accepted.**

- Attitude does affect Intention in the case of Purchase decisions regarding Necessity goods since the t-value is 1.957 – above a threshold. This way **H7 is accepted.**

- Subjective norms do not have a significant influence on purchase intention in the case of Luxury goods, t-value is very close to the threshold, however, not sufficient to prove significance. Therefore **H9 is rejected.**

Most importantly, the results of the bootstrapping revealed that Anticipated emotions **do** impact attitude regarding purchase decisions of both necessity and luxury items, however, that the influence is different: Positive Anticipated Emotions **do not have** a significant influence on Attitude in the case of Purchase decisions about Necessity goods, while matter a lot in the case of Luxury goods. For Necessity goods, on the contrary, Negative Anticipated Emotions **have** a significant influence on Attitude in the case of Purchase decisions about Necessity goods, while for Luxury goods they do not matter that much. In other words, the main hypotheses are confirmed.

Step 3 *Calculation of R2-value* - square of the correlation between actual and predicted values, that shows the predictive power of the model. As explained before, the value varies from 0 to 1, the higher the value - the higher is the predictive accuracy.

Table 5-20. *R2 value results for Necessity goods.*

Construct	R Square
ATT_N	0.342
INT_N	0.155

Table 5-21. *R2 value results for Luxury goods.*

Construct	R Square
ATT_L	0.148
INT_L	0.117

For the marketing field, R2 values of 0,67 0,33 and 0,19 for endogenous latent variables may be respectively described as substantial, moderate, or weak (Chin 1998, p.323).

The numbers can be explained by the limitations of the TRA model, described in the literature review. This model was taken as a base for the tested conceptual model. The intention has a low number of determinants. Moreover, this can be a weakness of the measures selected for the questionnaire.

Overall, weak R square values are normal, because there is a low number of constructs and pointing paths within the model.

Step 4 *Calculation of f2-value* – effect size. This value is the way to evaluate whether omitted construct has a substantive impact or not on the exogenous construct.

Table 5-22. *f2-values for Necessity goods case.*

	ATT_N	INT_N
ATT_N		0.026
INT_N		
NAE_N	0.448	
PAE_N	0.013	
SN_N		0.068

Considering theoretical guidance, f2 shows whether a latent variable has a weak, medium, or large effect at the structural level. This way in case of Necessity goods:

- “Negative Anticipated Emotions” has a large effect on “Attitude”;
- “Positive Anticipated Emotions” has no effect on “Attitude”;
- “Attitude” a small effect on “Intention”;
- “Subjective Norms” have a small effect on “Intention”.

Table 5-23. *f2-values for Luxury goods case.*

	ATT_L	INT_L
ATT_L		0.057
INT_L		
NAE_L	0.051	
PAE_L	0.075	
SN_L		0.011

- "Negative Anticipated Emotions" has a small effect on "Attitude";
- "Positive Anticipated Emotions" has a small effect on "Attitude";
- "Attitude" a small effect on "Intention";
- "Subjective Norms" does not have an effect on "Intention".

Most importantly, f2-values results are consistent with all previous analyses.

Step 5 *Calculation of Q2-value* – predictive relevance.

Q2 values more than 0 indicate that model has predictive relevance, while values below 0 indicate a lack of predictive relevance (Hair, Hult, Ringle & Sarstedt, 2016). This value is calculated by applying the blindfolding process in SmartPLS. The results of Blindfolding for both datasets are present in table 5-24.

Table 5-24. *Q2-values for necessity goods case.*

	SSO	SSE	Q^2 (=1-SSE/SSO)
ATT_N	2.233.000	1.842.877	0.175
INT_N	609.000	517.409	0.150
NAE_N	1.827.000	1.827.000	
PAE_N	1.218.000	1.218.000	
SN_N	609.000	609.000	

Since all Q2 values are above 0, predictive relevance for endogenous latent variables is ensured. The same applies to luxury goods (table 5-25).

Table 5-25. *Q2-values for luxury goods case.*

	SSO	SSE	Q^2 (=1-SSE/SSO)
ATT_L	2.233.000	2.057.059	0.079
INT_L	609.000	543.562	0.107
NAE_L	1.827.000	1.827.000	
PAE_L	1.218.000	1.218.000	
SN_L	609.000	609.000	

Step 6 in this research was not developed due to irrelevance, as clarified in the previous chapter.

5.7. Multigroup Analysis

Since we are comparing two groups of goods: necessity versus luxury, it is very convenient to use Multi-Group-Analysis in SmartPLS 3 software.

The multi-group analysis allows testing if there are significant differences between pre-defined data groups in their group-specific parameter estimates (e.g., outer loadings, path coefficients).

To run MGS, data preparation is required. I will use the “Generate data group” option in smart PLS. According to guidelines: This option allows the definition of groups of data for group-specific analyses. To split the group, I will add the new binary variable “MGA” with 1 - necessity or 0- luxury group category.

We will be running MGA on 2 groups (according to two good typologies) with 203 samples each. SmartPLS provides outcomes of three different approaches that are based on bootstrapping results from every group. The same settings as before for Partial Least Square and Bootstrapping are adopted. Bootstrap was done with 5000 sub-samples.

The results of the Multi-Group analysis are present in table 5-26.

Table 5-26. *Results of MGA: statistical parameters, t- and p-statistics.*

	Path Coefficients Original (GROUP_N)	Path Coefficients Original (GROUP_L)	Path Coefficients Mean (GROUP_N)	Path Coefficients Mean (GROUP_L)	STDEV GROUP_N	STDEV GROUP_L
ATT -> INT	0.170	0.265	0.172	0.213	0.088	0.135
NAE -> ATT	0.557	0.217	0.558	0.029	0.058	0.291
PAE -> ATT	0.094	0.263	0.132	0.335	0.074	0.101
SN -> INT	0.279	0.118	0.277	0.149	0.073	0.090

	t-Value (GROUP_N)	t-Value (GROUP_L)	p-Value (GROUP_N)	p-Value (GROUP_L)
ATT -> INT	1.969	2.017	0.049	0.044
NAE -> ATT	9.543	0.744	0.000	0.457
PAE -> ATT	1.276	2.594	0.202	0.010
SN -> INT	3.832	1.305	0.000	0.192

The most interesting numbers from bootstrapping to pay attention to are p-values. We can see that relationship between Attitude and Intention does not differ between groups: Attitude affects purchase intention regardless of good typology. Surprisingly, subjective norms have a significant influence in the case of necessity goods only, but this phenomenon will be discussed later.

Moreover, when it comes to Anticipated Emotions, the effect is completely different: Negative Anticipated Emotions NAE strongly affects attitude in case of necessity goods and does not has a significant influence on Attitude for Luxury goods. With Positive Anticipated Emotions (PAE) situation is the opposite: significant influence for Luxury goods and no influence for necessity goods.

Results are consistent with previous analysis which confirms that MGA was executed correctly.

We can see the difference between groups, but how can we ensure whether that difference is significant? To do so, the algorithm takes the difference in path-coefficients and implements p-statistic for obtained numbers. The results of this procedure are reported in table 5-27.

Table 5-27. *Path coefficient difference p-statistics.*

	Path Coefficients-diff (GROUP_L - GROUP_N)	p-Value original 1-tailed (GROUP_L vs GROUP_N)	p-Value new (GROUP_N vs GROUP_L)
ATT -> INT	0.095	0.257	0.513
NAE -> ATT	-0.340	0.952	0.096
PAE -> ATT	0.169	0.100	0.199
SN -> INT	-0.161	0.910	0.181

Similarly, when p-values are lower than 0.1 we can say that the results are significant. The significant differentiator between groups is NAE construct (p-value = 0.096). In other words, the effect of Anticipated Emotions on Attitude depends on group typology (necessity vs luxury), especially due to the differences in Negative Anticipated emotion effects.

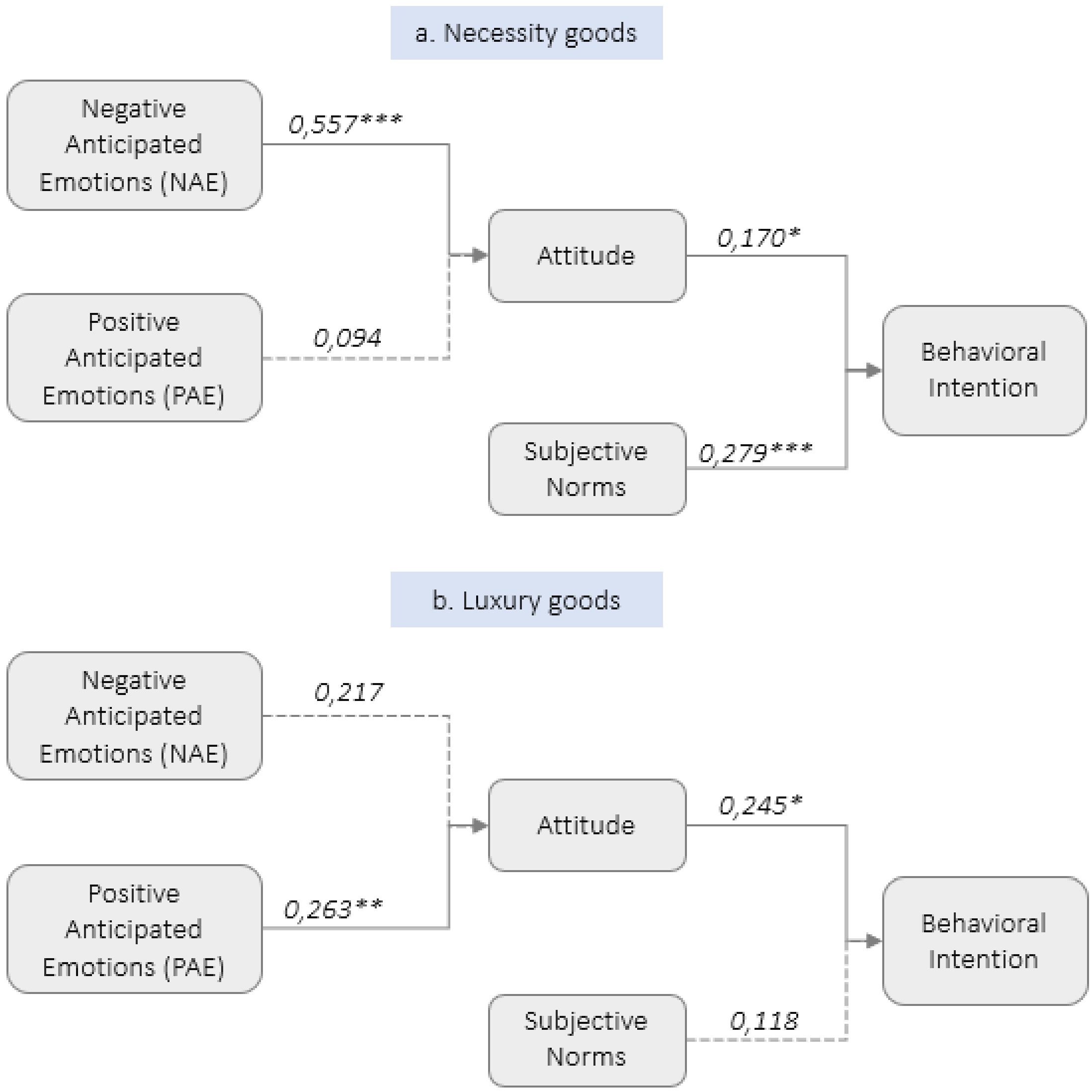
MGA allows to make conclusions regarding ***H1:*** *The effect of Anticipated Emotions on Attitude varies depending on good typology: necessity vs luxury.* We can consider this hypothesis **validated** and **confirmed**, noting that a significant difference is present in the NAE -> Attitude relationship.

5.8. Conclusions

At this point, the assessment of the proposed hypothesis and conceptual model is completed. The evaluation of the outer (or measurement model) allowed us to ensure reliability and validity of the conceptual model, while the evaluation of the inner (or structural model) allowed us to analyze the relationship between latent variables and the strength of those relationships. Finally, Multi-Group analysis demonstrated the difference between Luxury and Necessity group typologies.

The following figure 5-13 shows comprehensive insights into the research model. The figure includes the most important measures: path coefficients (β) with p-values that represent the strength of the relationship.

The dotted arrows between the constructs represent the not-validated hypotheses. The number of asterisks close to the path coefficients reflects the p-values (Mura, Lettieri, Radaelli & Spiller, 2016).



Notes: * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$.

Figure 5-13. Conceptual Model with path coefficients and p-values (a – Necessity goods, b – Luxury goods).

Figure 5-13 allows to review and provide final considerations regarding the research hypothesis. The very short summary is present in table 5-28.

Table 5-28. *Conclusions on research hypothesis.*

Hypothesis	*Numerical evidence*	*Outcome*
H1: *The effect of Anticipated Emotions on Attitude varies depending on good typology: necessity vs luxury.*	MGA analysis revealed the differences between the 2 groups. However, only for NAE, the difference was significant (p = 0.096).	**Partially Accepted**
H2: *Negative Anticipated Emotions (NAE) have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.*	Bootstrapping confirmed significant influence of NAE on Attitude with t = 9.687, p < 0.0001	**Accepted**
H3: *Positive Anticipated Emotions (PAE) do not have a significant influence on Attitude in the case of Purchase decisions about Necessity goods.*	Bootstrapping confirmed the absence of a significant relationship with t = 1.158, p = 0.236	**Accepted**
H4: *Positive Anticipated Emotions (PAE) have a significant influence on Attitude in the case of Purchase decisions about Luxury goods.*	Bootstrapping confirmed significant influence of PAE on Attitude with t = 2.540, p = 0.011	**Accepted**
H5: *Negative Anticipated Emotions (NAE) do not have a significant influence on Attitude*	Bootstrapping confirmed the absence of a significant influence of NAE (t = 0,757, p = 0.449)	**Accepted**

(continued)

in the case of Purchase decisions about Luxury goods.		
***H6:** Attitude towards Necessity good influences Purchase Intention*	Significant influence confirmed with t = 1.957, p = 0.049.	**Accepted**
***H7:** Attitude towards Luxury good influences Purchase Intention*	Significant influence confirmed with t = 2.059, p = 0.040	(continued) **Accepted**
***H8:** Subjective norms influence Behavioral Intention regarding the purchase of Necessity goods.*	Significant influence of SN on Intention confirmed with t = 3.775, p < 0.0001.	**Accepted**
***H9:** Subjective norms influence Behavioral Intention regarding the purchase of Luxury goods.*	Data analysis revealed the absence of significant influence of SN on Intention with t = 1.277, p = 0.202	**Not validated**

To conclude, seven out of nine hypotheses were validated and confirmed, one was partially accepted (H1) because only one construct (negative anticipated emotions) out of the expected two showed the significant difference between the two groups. One hypothesis (H9) was not validated: results revealed numbers that were on the threshold and it is not enough for accepting the hypothesis.

Overall, results fully meet the research objective and generate some reflections and discussions as well as valuable insights. More detailed results discussion will be presented in the following chapter.

Chapter 6.

6. CONCLUSIONS AND DISCUSSION

This dissertation was born with the objective to examine the impact of a consumer's positive and negative anticipated emotions on a purchase decision depending on the good category (necessity vs luxury) through self-reported emotions evaluation.

To accomplish this goal, the study has required several steps: **a structured literature review, the design of the research conceptual model, the empirical research, and the test of research hypotheses.**

This research topic emerged from the knowledge gap that was found during a detailed examination of the current state of knowledge. The literature review was the **first step** of this dissertation and included prior research done in the field of consumer psychology starting from the 1970s to-80s. The theoretical part was divided into three main blocks.

Firstly, the description of the most influential behavioral models: Theory of Reasoned Action (TRA) and its extension – Theory of Planned Behavior (TPB), which are conceptualizing how the behaviors are formed.

Secondly, the role of emotions in the process of behavior formation was discussed. Scholars have realized that apart from rational reasons there are irrational components that affect individual choices. This part will describe major conclusions on emotions made over the last 50 years by the worldwide research community, highlighting the ones particularly relevant for business and marketing applications.

Finally, the concept of Anticipated Emotions was introduced and discussed in detail. Not only current feelings are relevant for behavior-formation, but also anticipation and savoring could play a great role. We had a look at the attempts to include Anticipated Emotions in existing behavioral models. For example, the Model of

Goal-Directed Behavior (MGB), which was build based on the abovementioned TRA and TPB by including Anticipated Emotions as one of the new model constructs. Moreover, this block of the literature review included prior research done in the field of Anticipated Emotions and discussed the differences in emotional responses, since the effect of emotions on behavior formation depends on many contextual factors.

During the literature review, we clearly saw a lot of evidence that Anticipated Effects are crucial and should be considered in the prediction of consumer behavior. Many researchers attempted to explain the role of anticipated emotions together with other affective stimuli on purchase decisions.

Despite the increasing effort, the majority of the studies are unable to generalize their findings and additional validations always have to be made for every new research setting. Moreover, while some studies have reported medium-large correlations between anticipated emotions and intentions (e.g., Richard et al., 1998), other studies have found a weak correlation (e.g., O'Connor & Armitage, 2003). There is a lack of understanding of how exactly AE affects intentions.

Furthermore, anticipated emotions not only play an important role in consumer behavior but also **depend on the type of purchase** towards which people have to make a decision. In other words, the impact of AEs may depend dramatically on what we are buying. For example, it was proven that experience-based purchases are affected by anticipated emotions way more than material-based ones (Kumar et al., 2014). Results of that study revealed, that for experience-based purchases anticipation was significantly different: people reported to be more happy, pleased, and excited rather than waiting for a material good. Furthermore, the authors state the anticipation increases the utility of the purchase.

However, researchers have never investigated before very promising dimension: whether the role of anticipated emotion varies depending on the good category necessity vs luxury.

Generally, research suggests that when it comes to necessity goods, buyers are taking into account only the price-quality ratio and price is usually a defining variable for the purchase decision (Bochanczyk-Kupka, 2019, p. 260). In other words, it is commonly accepted that regarding purchase decisions in case of necessity goods only rational variables (like price) are taken into account and the emotional side is mostly neglected. On the contrary, for luxury goods, it is widely accepted to assume that emotional effects play a crucial role in a purchase decision (Kim et al., 2016; Makkar, 2014).

Therefore, it could be possible that for **necessity goods AEs might not imply** at all since the purchase might be done instinctively. Moreover, essentials (like food or water) for consumers are frequently purchasing products and the role of AEs is questioned. Some respected scholars raised similar questions:"The frequent purchases might be instinctive and not imply AEs. In this sense, the research could investigate the role of AEs in frequent or unprompted purchases..." (Bagozzi et al., 2016)

Unlikely, for **luxury goods the AEs might** have totally different impacts, or, even **play a key role** regarding a purchase decision. Effects of AEs on luxury goods have never been studied in detail:*"AEs emerge as a broad field of study with many avenues for additional research like luxury purchases*" (Bagozzi et al., 2016)

There is clearly a gap in knowledge regarding the role of AEs for purchase decisions towards luxury and necessity goods. Having a better understanding of that, would not only bring value to academic research worldwide but also get much better insights to the managers and help them influence the desired behavior.

This way the initial research idea was born to distinguish the impact of anticipated emotions depending on necessity vs luxury goods typology. Going further in reflections, I assumed that valence may help differentiate: the role of Positive AEs and Negative AEs for these two product categories might be completely different. Necessity good purchases might be mostly motivated by negative AEs, by the fear of stop having something we can not imagine our lives without. On the contrary, for luxury goods, positive AEs might have a key role: satisfaction, excitement, and pride consumers will feel by anticipating having luxury items.

To validate these assumptions, the **second step** was required: conceptual model development. I have started from understanding how anticipated emotions influence purchase decisions in general, leaving aside the part with luxury versus necessity goods distinction. As a base, the most influential theory in the field of consumer behavior was taken: TRA - Theory of Reasoned Action (Fishbein M. & Ajzen I., 1980)

The second challenge was to properly integrate Anticipated Emotions in the framework: do they have a direct influence on behavioral Intention or rather play a role through a mediator? After researching debates and diverse perspectives, I have decided to adopt the point of the original TRA authors that stated that affects and emotions "can be considered as background factors that influence beliefs and evaluation and can have an indirect effect on intentions and behavior, only mediated by theory's components." (Fishbein and Ajzen, 2010, p. 294) In other words, they rejected the idea that anticipated emotions can have a direct effect on behavioral intentions and presented empirical evidence in the study from 2013 (Ajzen and Sheikh, 2013).

The last step in the conceptual model development was to add the good typology: necessity vs luxury as moderator. This will allow us to spot the differences and gain deeper insights into how AEs affect purchase intentions. Together with the conceptual model, nine research hypotheses were proposed.

The **third step** of this dissertation included empirical research. At first, I had to understand how exactly I can test the conceptual model and proposed hypothesis in the most reliable way. The decision was made to use self-reported emotions, therefore develop a survey with questions that will reliably represent the model variables. Based on previous works, scales were reasoned and selected. To the NAE construct 10 scales were assigned, 7 to PAE, 11 to Attitudes, 3 to Subjective norms, and 3 to intentions. In total, there were 73 questions, 5 in the demographics section and two sets of 34 in the main section.

The surveys were implemented using the google forms tool (forms.google.com) and distributed through private e-mails to a target sample, social media platforms (e.g. Facebook, Linked In), online research forums.

In total for data analysis, 203 complete responses were used. The majority of respondents (87,7%) were Young Adults and belong to the Age group 18-34, most of them were young professionals – employed (48,3%), or, students (32,5%). The gender was balanced and the majority were from the territory of Europe with only 2,9% of replies outside of Europe. Group was very heterogeneous, which significantly reduced possible moderating effects from demographic variables and allowed to focus entirely on the differences between necessity and luxury goods, which are at the core of the research question.

Before processing the obtained data, the reliability of the questionnaire was checked. Even if all questions were formulated based on existing studies and were pre-tested, the research setup and context are slightly different. Reliability check included evaluation of internal consistency for all scales adopted. Each construct was measured through at least 3 questions, in total 32 scales for each good typology, and for ensuring internal consistency of those scales, alpha was checked and had proven to be reliable.

Forth step of research included data analysis using SMAT-PLS methodology. In particular, descriptive statistics, Measurement model (or inner model) analysis to validate a relationship between measured/observed variables and latent variables in the model, structural model (or outer model) analysis to understand a relationship between conceptual model's latent variables. In this study reflective approach was adopted.

A brief look at the descriptive statistic revealed some interesting early observations. Looking at means (μ) of different measures, we could see how different emotions were anticipated a lot more or a lot less than others. For example, in the case of Necessity goods people were not feeling much excited (μ = 2.32) or, proud (μ = 2.32), but more satisfied (μ = 4.00) and self-assured (μ = 4.08). Among all AEs the highest mean value had NAE_9 (uncomfortable) with μ = 5.12, which means that in case of not-purchasing necessity goods people are expected to feel instances of fear.

For Luxury goods, the picture was very different: we can observe that positive anticipated emotions are present to a very high extent (all mean values are closer to maximum - 7). However, the measure "self-assured" turned out to be an "outsider" with a mean of only μ = 4.631. It could lead us to a better understanding of why people buy luxury goods in the first place. Luxury is defined as "something more than necessary and ordinary", therefore does not lead to "self-assurance" that much. At the same time, for luxury goods, respondents did not anticipate many negative emotions (all mean values are closer to minimum - 1), only "sad" and "disappointed" (both with mean = 2,8) can be noticed.

This is giving us insights into what exact emotions are more involved in the decision-making process for different product typologies and may allow designing behavioral interventions and marketing communications more effectively.

Measurement model analysis included checks of (1) internal consistency reliability (Composite Reliability, Cronbach's alpha), (2) convergent validity (outer loadings, AVE), and (3) discriminant validity (Cross-loadings, Fornell-Larcker criterion, and Heterotrait-monotrait ratio). The model has successfully passed all the checks. During the analysis, with the aim to improve model reliability and validity, one measure (out of 7) for Positive Anticipated emotions was excluded and one (out of 10) for Negative. Knowing that in the reflective measurement model all indicators are interchangeable, this minor adjustment can not worsen the overall model performance.

Overall, after ensuring internal consistency, convergent and discriminant validity, it was concluded that the outer model is properly executed and can be used for validating relationships between constructs using PLS and Bootstrapping.

The main source of insights was *structural model analysis*. After interpreting the results in the light of the literature review, we might find confirmations for an existing opinion as well as some controversial points that are shifting and deepening the commonly accepted understanding of the role of emotions in purchase decisions. Results provided answers to the questions that were raised but never answered before.

Despite common assumptions that for necessity goods AEs might not imply at all since the purchase might be done instinctively, PLS path-coefficients revealed that anticipated emotions **do have a significant influence** on attitude, however, only negative ones (with t = 9.687, p = 0.000). In other words, anticipating negative emotions has a positive effect on attitude. For example, people expect to feel uncomfortable if they fail to buy this product, which makes them consider this product “useful” and “effective” and buying it “intelligent” and “wise”.

This finding confirms the importance of emotions even where at first sight they are not relevant and purchase may be assumed to be driven purely by rational components.

For Necessity goods, both Attitude and Subjective Norms had a significant influence on behavioral Intentions (with t = 1.957, p = 0.049 and t = 3.775, p = 0.000 respectively). According to the Theory of Reasoned Action (TRA), Intentions are a function of Attitudes and subjective Norms. These results confirm one more time good predictive abilities of the TRA framework, from which these relationships were taken.

For Luxury goods, anticipated emotions affected attitude completely differently: the significant influence of positive anticipated emotions on attitude was found with bootstrapping (t = 2,540, p = 0.011). However, for Negative ones the significant influence was not confirmed (t = 0.757, p = 0.449). This means that people are mostly driven by anticipation of being “excited”, “delighted”, “proud”, etc. At the same time, negative emotions like “anger” or “sadness” are not very relevant for luxury purchases. It does not argue with the current literature but underlines the importance of positive AEs for luxury goods, for example, marketing communications.

Regarding other constructs taken originally from the TRA model, results revealed the following. Attitude had a significant influence on Intention (t = 2.059, p = 0.040).

However, bootstrapping results did not provide sufficient evidence for the influence of Subjective norms ($t = 1.277$, $p = 0.202$).

So, “what others think” does not impact attitude towards luxury goods according to respondents. This result could be explained by the demographic characteristics of the sample group. Among respondents, the vast majority were young professionals from Europe. There are more and more discussions at a worldwide level about a hypothesis according to which this age group has a higher tendency for independence and within a given cultural context there is a trend to “care less about the opinion of others”. The aforementioned hypothesis is outside the scope of this study however, it represents an opportunity for future work.

Overall, findings fully satisfied the research objective to examine and understand the impact of a consumer’s positive and negative anticipated emotions on a purchase decision depending on the good category (necessity vs luxury).

To conclude, we can extract valuable insights both for academic and managerial implications.

6.2. Academic implications

Firstly, the systematic literature review provides a solid understanding of the current role of emotions in consumer behaviors and highlights not only main discoveries over the last 50 years but also many unanswered questions and knowledge gaps that may be used by other researchers to formulate relevant research questions. This way also the lack of understanding of mechanisms behind the effect of anticipated emotions was identified.

It was questioned but never studied before whether anticipated emotions apply to necessity goods and whether the effects depend on the good category: necessity versus luxury at all. This study wants to contribute to closing this knowledge gap and the objectives are achieved. After interpreting the results in the light of the literature review, we might find confirmations for an existing opinion as well as some controversial points that are shifting and deepening the commonly accepted understanding of the role of emotions in purchase decisions.

To begin, let’s discuss first **how AEs contribute to intention formation**? What mechanism exactly is behind it? It is important to understand that if we want to exploit the usage of Anticipated emotions to design successful behavioral interventions. Researchers have different opinions on that:

1. AEs do not influence intention;
2. AEs influence intention directly;
3. AEs influence intention through mediators (e.g. Attitude).

The first point of view is already outdated since it is a widely accepted fact that AEs are relevant contributors to the process of behavioral formation and mane pieces of evidence of this influence were found(Bagozzi et al., 2016). In any case, the results of this study confirmed again the relevance of Anticipated Emotions in behavior formation.

The second point of view was present in one of the most popular frameworks in the consumer behavior field - the Model of Goal-Directed Behavior (MGB) (Perugini & Bagozzi, 2001c), which was build based on TRA and TPB models and included Anticipated Emotions as one of the new model constructs. The third point of view was proposed by authors of the original TRA model: “emotions can be considered as background factors that influence beliefs and evaluation and can have an indirect effect on intentions and behavior, only mediated by theory’s components.” (Fishbein and Ajzen, 2010, p. 294) In other words, they rejected the idea that anticipated emotions can have a direct effect on behavioral intentions and presented empirical evidence in the study from 2013 (Ajzen and Sheikh, 2013). The results of my thesis support the third point of view and have shown that **AEs effects can be successfully considered through the Attitude construct.**

Moving on, it is accepted that for some products anticipated emotions do not apply at all. For example, necessities, since “the frequent purchases might be instinctive and not imply AEs” (Bagozzi et al., 2016). The results of this study argue with that and had shown significant influence of negative anticipated emotions on attitude for necessity goods (with t = 9.687, p = 0.000). That means, we can not say anymore that necessity goods purchase decisions are purely rational and do not involve emotions. This insight has also managerial implications that will be mentioned later.

Another value this study brings to researches is the evidence of the fact that the effect of AEs on purchase intention **depends on what we buy**. Multi-group analysis revealed that there is a significant difference in p-values between necessity and luxury good category for negative AEs effects (p = 0.096). Many other parameters can be taken as a moderator: maybe, AEs effect depends also on the personal characteristics of the decision-maker, or, context? This level of detalization is not yet present in the young and fast-developing field of Anticipated Emotions. However, with this study first steps towards a better understanding of “on what AEs may depend on” were made. The product typology (necessity vs luxury) was proven to be an effective classification.

Additionally, the effectiveness of the TRA model was confirmed again. For Necessity goods, both Attitude and Subjective Norms had a significant influence on behavioral Intentions (with t = 1.957, p = 0.049 and t = 3.775, p = 0.000 respectively). Attitude had a significant influence on Intention (t = 2.059, p = 0.040) also in the case of luxury goods, and even if bootstrapping results did not provide sufficient evidence for the influence of Subjective norms (t = 1.277, p = 0.202), the possible reasons behind were explained above. Overall, the TRA model as a base framework showed sufficient performance.

One more important note about TRA model. There was no significant difference found with MGA analysis between necessity and luxury goods in the relationship Attitude – Intention (p-value of the difference = 0.513) and Subjective Norms - Intention (p-value of the difference = 0.181). That proved that model is very universal and performs well in diverse contexts.

Finally, the 406 - samples dataset generated by this study will be available by request to any successive empirical researcher. For instance, to deepen the understanding of AEs effects, one may use this data to test demographical variables as moderators and figure out how consumer behavior formation varies depending on age, gender, country of origin, occupation or annual income.

6.3. Managerial implications

This study contributes not only to academic research but also helps firms who are searching for answers. Managers are always willing to get deeper insights into consumer behavior. In particular, understand how do people make purchase decisions. Why sometimes they prefer our product to another? What do people consider while making their choice? Price? Other rational components? Emotions? Researchers have already provided evidence that emotions are relevant in the decision-making process (detailed description in the theoretical chapter). However, the discussion was usually focused on the current emotions, and this study focused on future-oriented ones: Anticipated emotions - perceived consequences of decision outcome.

When it comes to necessity goods, there are low-cost products purchased by consumers so often that they became a habit, thus being bought without much thought given (e.g., toilet paper, ketchup, soap). As a consequence, customers often pick a brand one time and then stick to it for long periods of time. If you are used to buying a brand of toilet paper, unless there is an extraordinary event or experience (e.g., a noticeable price increase), you will continue doing it. As mentioned before in the thesis, researchers are suggesting that necessity purchases are rational (Bochanczyk-Kupka, 2019), thus emotions have no impact in purchasing decisions. However, there is a simple example contradicting this theory. Some years ago, there was intense marketing for toilet paper with a flushable toilet roll. Those advertisements were focused on removing customer's stress and anxiety caused by the pile of rolls gathering in the bathroom, all by having a flushable solution. The success behind this innovation was impacted by a marketing approach focused on emotions. This thesis proves that the aforementioned example is not an exception, but rather an example supporting the proven hypothesis.

Despite not being straightforward at first, this research revealed the significant influence of negative anticipated emotions on attitude for necessity, which proves to be a useful tool for managers and especially marketing specialists. On the other hand, communicating positive anticipated emotions will not be that effective, since their impact on attitude is insignificant.

Moreover, this study provides even deeper insights by looking at means (m) of different measures of emotions. We can relatively compare which emotions were self-reported as more present. For example, in the case of Necessity goods people were not feeling much excited (m = 2.32) or, proud (m = 2.32), but more satisfied (m = 4.00) and self-assured (m = 4.08). Among all AEs the highest mean value had negative AE "uncomfortable" with m = 5.12, which means that in the case of not-purchasing necessity goods people are expected to feel instances of fear.

In terms of marketing, wide-scale promotions focused around NAE can benefit both the product and the brand image overall. However it is more than just marketing, these results can be put at the basis of product innovation for necessity goods. Customers do not react to new features, but the benefits they bring. Now it's clear that benefits should aim towards eliminating possible negative emotions.

In terms of luxury goods, the impact of anticipated emotions is the opposite compared to the necessary ones. Study results revealed a significant influence of positive anticipated emotions on the attitude. Managers can use this to design effective marketing communication for luxury goods, underlying how excited and delighted you will feel in case of acquiring the product, highlighting instances of joy (Happy, Glad, Satisfied) and pride (Proud and Self-Assured). However, highlighting negative anticipated emotions might not work that well: the results showed that the effect of those emotions on attitude is insignificant. While this might seem obvious, the new variable brought to light by this research is the lack of impact caused by subjective norms.

There are commercials for luxury goods such as cars focused on what your neighbors or friends have. These examples lead to experiencing negative emotions such as jealousy or thinking that from a subjective norm perspective, it would be all right to purchase something similar as well. However, NAE and subjective norms have an insignificant impact, thus managers and marketing experts could use these results for creating more appealing messages for customers. Purchasing luxury goods should be a decision based on firstly understanding what makes you feel good and then trusting your instincts and going for it despite other people's opinions.

There is a current trend around living your life and making a decision based on what is good for you, without considering too much the opinion of the ones around. This goes along well with the results presented within this thesis and managers should take advantage by combining them. An example of a brand with a marketing strategy in line with the conclusions of this research is Apple. From a behavioral perspective, as publicly stated, for individuals with an age between 18-45 years old, Apple products provide a sense of achievement and belonging, together with self-expression(Dudovskiy, 2021).

For luxury goods, respondents anticipated the least emotions such as "sad" and "disappointed", however expected much more to feel Excited, Delighted, Happy, Glad, and Satisfied. These distinctions may allow designing behavioral interventions more effectively.

Overall, this research made a step towards understanding nuances associated with capturing emotions in attitude-based models for marketing decision-making. The conceptual model proposed explained these effects in case of necessity vs luxury goods very well and might be used to perform tests for other product categories, even for specific product typology if needed.

Apart from particular insights, this study is bringing additional value because it can be replicated: a model designed together with measures selected and questionnaire used can be adopted for testing any other product typologies, even specific product lines. This way managers and practitioners can have a reliable method to get specific insights on consumer behavior and choices within the context they need.

Chapter 7.

7. LIMITATIONS AND FUTURE WORK

Even if this study contributes to academic research and provides insight for practitioners, it is also affected by limitations that arising from theoretical and empirical research. Those limitations, however, provide also opportunities for further investigation. This chapter will describe the main limitations together with future research opportunities.

First of all, limitations arise from the method used to assess emotions: the self-reported technique. The problem is that this method can **detect only conscious emotional experiences** that consumers can recognize and report, leaving aside all unconscious emotions that occur without individual awareness (Bettiga et al., 2020b) To solve this problem, physiological measures can be adopted. Emotion, mood, and stress recognition (EMSR) can use multiple sources to gather unconscious signals of our body. For example, from facial expression (Fasel and Luettin, 2003), speech (El Ayadi et al., 2011), full-body motion (Kleinsmith and Bianchi-Berthouze, 2013) we can receive some hints and analyzed based on patterns what emotions the person is truly experiencing. Also, electrical brain activity detected with electroencephalogram (EEG), cardiac activity measured by an electrocardiogram (ECG), skeletal muscle electrical activity (Electromyography, EMG) can occur as an effective technique for emotion evaluation.

Applying psychological emotions evaluation techniques to the context of purchase decision toward luxury and necessity goods, the results of the study presented herein can be extended and deepened. For example, In the systematic review of the wearable systems used to assess the affect in ambulatory conditions by Wac and Tsiourti (Wac & Tsiourti, 2014), list criteria for the device choice and accurate guidelines are provided based on deep analysis of existing options. Moreover, by combining the self-reported techniques with physiological ones, we can obtain a full picture of anticipated effects on purchase intentions.

Another limitation is connected with the abovementioned one: the **subjectivity factor** introduced by the survey. Not only the usage of the self-reported technique brings it in, but also the absence of a common united perspective on the concept of Anticipated Emotions. Scholars are still adopting different measures and there is no clear idea of what works the best. In this study, measures introduced by Bagozzi and colleagues (Perugini & Bagozzi, 2001d) were used and proved to be valid and reliable. However, for this context 2 indicators (out of 18) were excluded and better situational usage of the measures could be developed in the future.

Another limitation is that the survey just **simulates** the context, without putting participants in a real-life situation. The direct observation of participants and evaluation of the purchase intention before the moment of real purchase would have improved the quality of the study too and reduce the subjectivity factor. However, it is not fully clear, when a person exactly experiencing anticipated emotions, the feeling can be distributed over days and weeks. This could be an interesting area of further investigation.

In this study, the focus was on the difference between product group categories: necessity versus luxury. However, many other promising directions can be found and explored. This study proved that AEs affects **depend on what we buy** (luxury or necessity goods), by Kumar and colleagues it was proven that there is a difference between experience-based and material-based ones (Kumar et al., 2014), other research line goes in the direction of distinguishing between hedonic and utilitarian goods (Bettiga et al., 2020b). Another dimension and **specific good categories** could be assessed in terms of emotional effects in the purchase decision making. For example, among material goods apart from consumer goods, it would be interesting to see AEs effects on purchase decisions towards the capital assets (like buildings or furniture) and among experiences and services, promising dimension is affected of savoring on vacation-related purchases (e.g. "can the anticipation of vacation increases it's value(Bettiga et al., 2020b)

Moreover, AE's affects may depend on the **individual characteristics of the decision-maker**. This study aimed to target in the empirical research a homogeneous group of people (mostly young adults from Europe) in order to receive a more clear distinction and keep the focus on the necessity vs luxury dimension. This can be an advantage, but at the same time limitation, because results can not be fully generalized and for other groups of individuals/ other geographical concentrations can be different. Form the other hand, this opens new dimensions for the research, and demographical variables (age, gender, country of origin, etc.) can be studied in the role of moderators.

Apart from differences between product good categories and individual characteristics, AEs affects may depend on the peculiar contexts. The promising area of study would be to spot and describe those contexts. For example, case of impulsive purchases, when consumers make instant spontaneous decisions. Is there a place for emotional effects in these contexts?

For further research it is worth mentioning also is the phenomenon that low values for the influence of subjective norms on the luxury goods purchase intention were obtained. It could be also possible that significant influence was not found due to the characteristics of the sample group. For example, young individuals may tend to aim for independence in decision-making, therefore they self-reported low effect of “opinions of other (=subjective norms). Or, this phenomenon could be explained by the peculiarities of luxury goods. Further investigation is required to understand it better.

Overall, the field of Anticipated Emotions is relatively young and the literature review revealed many gaps in the current state of knowledge. Even if some of the questions were answered by this study, there are many other promising directions.

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ANNEX

Annex 1. *Descriptive statistics.*

a) *Necessity goods indicators (sample size: 203).*

Indicator	Range	Mean (μ)	Median	St.Dev.(σ)
PAE_1	(1-7)	2.330	2.000	1.490
PAE_2	(1-7)	2.680	2.000	1.652
PAE_3	(1-7)	2.961	3.000	1.744
PAE_4	(1-7)	3.202	3.000	1.829
PAE_5	(1-7)	3.990	4.000	1.922
PAE_6	(1-7)	2.320	2.000	1.502
PAE_7	(1-7)	4.079	4.000	1.981
NAE_1	(1-7)	3.734	4.000	2.195
NAE_2	(1-7)	4.562	5.000	2.032
NAE_3	(1-7)	3.586	3.000	2.121
NAE_4	(1-7)	3.286	3.000	2.137
NAE_5	(1-7)	3.906	4.000	2.167
NAE_6	(1-7)	4.281	4.000	2.052
NAE_7	(1-7)	2.877	2.000	2.115
NAE_8	(1-7)	4.251	5.000	2.082
NAE_9	(1-7)	5.108	6.000	1.835
NAE_10	(1-7)	3.212	3.000	2.096
ATTITUDE_1	(1-7)	6.241	7.000	1.367
ATTITUDE_2	(1-7)	5.847	7.000	1.525
ATTITUDE_3	(1-7)	5.488	6.000	1.714
ATTITUDE_4	(1-7)	5.384	6.000	1.588
ATTITUDE_5	(1-7)	4.690	4.000	1.633
ATTITUDE_6	(1-7)	5.394	6.000	1.519
ATTITUDE_7	(1-7)	4.276	4.000	1.731

(continued)

ATTITUDE_8	(1-7)	3.724	4.000	1.674
ATTITUDE_9	(1-7)	3.207	3.000	1.695
ATTITUDE_10	(1-7)	3.483	4.000	1.623
ATTITUDE_11	(1-7)	3.739	4.000	1.869
SN_1	(1-7)	5.980	7.000	1.678
SN_2	(1-7)	5.877	7.000	1.713
SN_3	(1-7)	5.872	7.000	1.671
INT_1	(1-7)	6.433	7.000	1.144
INT_2	(1-7)	6.409	7.000	1.134
INT_3	(1-7)	6.419	7.000	1.139

b) *Luxury goods (sample size: 203).*

Indicator	Range	Mean (μ)	Median	St. Deviation (σ)
PAE_1	(1-7)	6.384	7.000	1.087
PAE_2	(1-7)	6.074	7.000	1.339
PAE_3	(1-7)	6.103	7.000	1.370
PAE_4	(1-7)	6.054	7.000	1.336
PAE_5	(1-7)	6.069	7.000	1.388
PAE_6	(1-7)	5.828	7.000	1.561
PAE_7	(1-7)	4.631	5.000	1.738
NAE_1	(1-7)	1.951	1.000	1.364
NAE_2	(1-7)	2.300	2.000	1.497
NAE_3	(1-7)	1.857	1.000	1.341
NAE_4	(1-7)	1.823	1.000	1.342
NAE_5	(1-7)	2.828	2.000	1.763
NAE_6	(1-7)	2.793	2.000	1.698
NAE_7	(1-7)	1.813	1.000	1.318
NAE_8	(1-7)	1.892	1.000	1.375
NAE_9	(1-7)	1.990	1.000	1.445

(continued)

NAE_10	(1-7)	1.700	1.000	1.213
ATTITUDE_1	(1-7)	4.039	4.000	1.652
ATTITUDE_2	(1-7)	3.759	4.000	1.698
ATTITUDE_3	(1-7)	4.084	4.000	1.783
ATTITUDE_4	(1-7)	3.837	4.000	1.455
ATTITUDE_5	(1-7)	5.138	5.000	1.613
ATTITUDE_6	(1-7)	3.793	4.000	1.514
ATTITUDE_7	(1-7)	5.759	6.000	1.457
ATTITUDE_8	(1-7)	5.808	6.000	1.385
ATTITUDE_9	(1-7)	5.887	6.000	1.415
ATTITUDE_10	(1-7)	5.709	6.000	1.537
ATTITUDE_11	(1-7)	5.837	6.000	1.445
SN_1	(1-7)	4.542	5.000	1.879
SN_2	(1-7)	4.143	4.000	1.785
SN_3	(1-7)	4.069	4.000	1.794
INT_1	(1-7)	3.606	4.000	1.966
INT_2	(1-7)	3.808	4.000	1.992
INT_3	(1-7)	3.680	4.000	1.968

Annex 2. *Outer loadings values.*

a) *Necessity goods dataset.*

Indicator	Related Construct (PAE_N)	Indicator	Related Construct (NAE_N)	Indicator	Related Construct (ATT_N)	Indicator	Related Construct (INT_N)
PAE_N_1	0.676	NAE_N_1	0.800	ATT_N_1	0.588	INT_N_1	0.996
PAE_N_2	0.739	NAE_N_2	0.800	ATT_N_2	0.728	INT_N_2	0.991
PAE_N_3	0.706	NAE_N_3	0.770	ATT_N_3	0.771	INT_N_3	0.991
PAE_N_4	0.603	NAE_N_4	0.808	ATT_N_4	0.664	Indicator	Related Construct (SN_N)
PAE_N_5	**0.376**	NAE_N_5	0.837	ATT_N_5	0.703	SN_N_1	0.976
PAE_N_6	0.738	NAE_N_6	0.762	ATT_N_6	0.745	SN_N_2	0.978
PAE_N_7	0.763	NAE_N_7	0.840	ATT_N_7	0.788	SN_N_3	0.981
		NAE_N_8	0.810	ATT_N_8	0.770		
		NAE_N_9	0.666	ATT_N_9	0.672		
				ATT_N_10	0.769		
				ATT_N_11	0.712		

b) *Luxury goods dataset.*

Indicator	Related Construct (PAE_L)	Indicator	Related Construct (NAE_L)	Indicator	Related Construct (ATT_L)	Indicator	Related Construct (INT_L)
PAE_L_1	0.797	NAE_L_1	0.645	ATT_L_1	0.791	INT_L_1	0.985
PAE_L_2	0.897	NAE_L_2	0.839	ATT_L_2	0.701	INT_L_2	0.977
PAE_L_3	0.899	NAE_L_3	0.576	ATT_L_3	0.753	INT_L_3	0.995
PAE_L_4	0.898	NAE_L_4	0.605	ATT_L_4	0.748	Indicator	Related Construct (SN_L)
PAE_L_5	0.880	NAE_L_5	0.943	ATT_L_5	0.789	SN_L_1	0.795
PAE_L_6	0.757	NAE_L_6	0.891	ATT_L_6	0.797	SN_L_2	0.847
PAE_L_7	0.561	NAE_L_7	0.546	ATT_L_7	0.678	SN_L_3	0.830
		NAE_L_8	0.560	ATT_L_8	0.763		
		NAE_L_9	0.606	ATT_L_9	0.755		
		NAE_L_10	**0.452**	ATT_L_10	0.722		
				ATT_L_11	0.720		

Annex 3. *Cross-loadings criterion.*

a) *Necessity goods dataset.*

	ATT_N	INT_N	NAE_N	PAE_N	SN_N
ATT_N_1	0.588	0.383	0.297	0.034	0.531
ATT_N_2	0.663	0.410	0.314	-0.092	0.516
ATT_N_3	0.703	0.401	0.404	0.084	0.583
ATT_N_4	0.745	0.315	0.400	0.012	0.453
ATT_N_5	0.788	0.217	0.544	0.065	0.407
ATT_N_6	0.769	0.327	0.419	0.028	0.535
ATT_N_7	0.673	0.056	0.354	0.355	0.182
ATT_N_8	0.769	0.069	0.460	0.353	0.169
ATT_N_9	0.713	0.100	0.485	0.350	0.153
ATT_N_10	0.728	0.034	0.454	0.286	0.139
ATT_N_11	0.771	0.097	0.405	0.339	0.266
INT_N__1	0.306	0.996	0.218	-0.000	0.350
INT_N__2	0.311	0.991	0.226	0.021	0.371
INT_N__3	0.309	0.991	0.218	0.006	0.364
NAE_N_1	0.492	0.166	0.800	0.230	0.206
NAE_N_2	0.484	0.220	0.800	0.301	0.332
NAE_N_3	0.417	0.153	0.770	0.170	0.195
NAE_N_4	0.450	0.134	0.808	0.114	0.211
NAE_N_5	0.521	0.166	0.837	0.178	0.190
NAE_N_6	0.426	0.237	0.762	0.113	0.280
NAE_N_7	0.487	0.104	0.840	0.148	0.071
NAE_N_8	0.411	0.201	0.810	0.127	0.227
NAE_N_9	0.396	0.215	0.667	0.204	0.366
PAE_N_1	0.032	-0.141	0.093	0.694	-0.227
PAE_N_2	0.105	-0.116	0.067	0.764	-0.087
PAE_N_3	0.113	-0.069	0.060	0.757	-0.096

(continued)

PAE_N_4	0.079	-0.101	-0.011	0.673	-0.076
PAE_N_5	0.083	-0.118	0.200	0.744	-0.189
PAE_N_6	0.267	0.176	0.298	0.729	0.244
SN_N_1	0.474	0.319	0.256	0.070	0.976
SN_N_2	0.500	0.383	0.283	0.017	0.978
SN_N_3	0.508	0.362	0.301	0.014	0.981

b) Luxury goods dataset.

	ATT_L	INT_L	NAE_L	PAE_L	SN_L
ATT_L_1	0.793	0.341	0.314	0.192	0.456
ATT_L_2	0.698	0.149	0.016	0.287	0.408
ATT_L_3	0.750	0.150	0.102	0.349	0.420
ATT_L_4	0.751	0.364	0.290	0.139	0.417
ATT_L_5	0.790	0.298	0.298	0.140	0.398
ATT_L_6	0.800	0.332	0.303	0.186	0.375
ATT_L_7	0.677	0.136	0.151	0.256	0.284
ATT_L_8	0.766	0.323	0.355	0.183	0.430
ATT_L_9	0.752	0.077	0.110	0.334	0.388
ATT_L_10	0.720	0.197	0.152	0.411	0.391
ATT_L_11	0.717	0.123	0.057	0.315	0.366
INT_L_1	0.316	0.985	0.492	0.230	0.238
INT_L_2	0.322	0.977	0.458	0.298	0.270
INT_L_3	0.331	0.925	0.476	0.251	0.255
NAE_L_1	0.042	0.367	0.654	0.223	0.033
NAE_L_2	0.134	0.420	0.842	0.190	0.060
NAE_L_3	-0.058	0.284	0.585	0.211	-0.040
NAE_L_4	-0.061	0.257	0.614	0.218	-0.090
NAE_L_5	0.268	0.416	0.943	0.276	0.119
NAE_L_6	0.233	0.437	0.892	0.263	0.069

(continued)

NAE_L_7	-0.034	0.289	0.555	0.202	-0.075
NAE_L_8	-0.007	0.339	0.569	0.205	-0.022
NAE_L_9	0.072	0.345	0.613	0.232	-0.010
PAE_L_1	0.252	0.142	0.189	0.806	0.072
PAE_L_2	0.298	0.226	0.231	0.893	0.185
PAE_L_3	0.280	0.223	0.248	0.912	0.150
PAE_L_4	0.275	0.251	0.262	0.896	0.210
PAE_L_5	0.232	0.196	0.157	0.759	0.143
PAE_L_6	0.233	0.249	0.264	0.584	0.168
SN_L_1	0.397	0.226	0.111	0.221	0.795
SN_L_2	0.448	0.200	0.097	0.177	0.847
SN_L_3	0.465	0.210	0.092	0.070	0.830