EFFECTS OF COGNITIVE BIASES AND THEIR VISUAL EXECUTION ON CONSUMER BEHAVIOR IN E-COMMERCE PLATFORMS

A Thesis

Presented to the Faculty

ISM University of Management and Economics

In Partial Fulfillment of the Requirements for the Degree of

Master in International Marketing

by

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May 2016

Abstract

The purpose of this research was to examine what effect cognitive biases and their visual execution has on consumer behavior in e-commerce platforms. Cognitive biases are behavioral concepts which are explaining human decision making deviation form rational means of judgement, when decisions could be made unconsciously in deeper patterns of human thinking. Since the main field of interest of this research is consumer behavior on e-commerce platforms, the means of visual execution of cognitive biases should also have been taken into account, since visual representation is highly important factor of information provision online. Therefore, to empirically test the concept interaction outcomes it was decided to conduct and experiment on working e-commerce website. After collecting data and running multiple regressions it was concluded that cognitive biases and their visual execution has significant effects on consumer behavior in e-commerce platforms: assessment of these concepts increased conversions and boosted visitor engagement.

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Introduction

Relevance of the Topic

Nowadays the internet is growing as fast as ever and is important part of most peoples' daily lives. World Wide Web is used for entertainment, studying, also, for business. Booming internet businesses together with breakthrough technologies led us to the age of so-called Big Data. Overwhelming amounts of metrics are collected every second. This enables us to take data analytics to a whole new level: almost every step of the customer can be tracked online. And not only steps and/or goal completions could be tracked online: even cursor or eye movement could be recorded. What is more, all this data could be used not only to better explain, but also to predict and in some cases even model customer behavior.

So, is customer irrationality considered while internet platforms are being optimized by business owners, site administrators, marketing managers and many others? Sadly, we still cannot answer this question with simple "yes" or "no". However, the concept of bounded rationality is booming now in the online businesses. Through big data analysis and advanced segmentation, online businesses owners are able not only to target their customers incredibly efficiently, but also to predict their behavior accurately and what is more, even to shape and push the audiences towards specific goals or decisions (Daugherty, Li, & Biocca, 2005) (Alexander, 2006).

To assess bounded rationality in online businesses, it is crucial to understand the reasons behind customers' actions, so that the most relevant information would be provided at right time in the right place. To add up, not only the information itself, but the means of visual execution of it matters (Daugherty, Li, & Biocca, 2005) (Biers & Richards, 2005) (Pellet & Papadopoulou, 2009). In other words, it is necessary not only to provide relevant information, but also do it in visually attractive way (Jennings, 2000).

It is very obvious, that online platform customers cannot smell, touch and feel the products in any way as they could in regular shop or store (Alexander, 2006) (Jiang & Benbasat, 2004). One and only mean of presenting product online is visual presentation. The evolution of online platforms and e-commerce sites resulted in various different ways and tests towards visual representation of products and services (Alexander, 2006). The main idea in this field was to provide as much visual experience as possible, to compensate for lost features (Jiang & Benbasat, 2004). Thus two main dimensions of visual manipulation could be identified: visual and functional. Under the first one, the goal is to show as many means of visual appearance as possible, and under the second one the goal is to present the functions and features of the products in a visually appealing way (Jiang & Benbasat, 2004). In terms of online platforms, the functional visual execution usually tends to be design, technical location of features and properties (Jiang & Benbasat, 2004) and functional – colors and similar means of content visualization (Jiang & Benbasat, 2004). The previous tend to take much more time to develop and is very different from platform to platform, whereas the latter, has clear means of optimal performance, is easy to adopt and manipulate (Jiang & Benbasat, 2004) (Lichtlé, 2007) (Allagui & Lamoine, 2008). What is more, colors tend to influence the human behavior and information perception in general, because of specific stimulating properties (Lichtlé, 2007) (Allagui & Lamoine, 2008) (McMullen, Hawick, Du Preez, & Pearce, 2012) which will be discussed in more details in the following parts of the research.

In this particular case of consumer behavior in online platforms (mostly e-commerce), the clash of two major streams of scholar research could be observed: psychology and cognitive biases together with studies on content visual execution in e-commerce platforms.

Cognitive biases as a field, is still being shaped by various scholars (Tversky & Kahneman, 1974) (Wilke & Mata, 2012) (Gigerenzer & David, 1987). More and more behavioral patterns are being registered as valid cognitive biases. The concept itself is accepted and discussed; however, none of scholars have taken cognitive biases to the field of online e-commerce; even though, the practicing professionals in this field are already applying strategies and tools, which could be classified as triggering cognitive biases of human thinking (Lim & Dubinsky, 2005) (Allagui & Lamoine, 2008) (Alexander, 2006). By deepening the understanding of possible cognitive biases effect on consumer behavior in e-commerce platforms, it would become easier to create platforms that are performing better and are appealing to the visitors more.

In this paper, the matter is addressed by investigating and unifying several behavioral models into one. The theory of cognitive biases will be explored; also, the analysis on visual execution practices in e-commerce platforms will be conducted. Out of this, the main research question emerges: how cognitive biases and their visual execution affect consumer behavior in e-commerce platforms. This research will help to understand and explore the relationship between the presence of visually appealing features triggering cognitive biases of human thinking and consumer behavior when exposed to such e-commerce platform attributes. What is more, the research will provide practical implications for site improvements and optimization.

Research Question, Goal and Objectives

The main question of this research could be stated as following: how cognitive biases equipped with different visual execution affect consumer behavior on e-commerce platforms? The ultimate goal of the research is to examine the impact of cognitive biases (taking into account their visual execution) on consumer behavior in e-commerce platform.

In order to achieve this research goal, following objectives were constructed:

1. To review academic literature on the main concepts used in this research such as behavioral cognitive biases, consumer behavior in e-commerce platforms and appearances of cognitive biases based tools in e-commerce platforms.
2. Create a model to test various cognitive biases and their visual execution in e-commerce platforms and effect it has on consumer behavior.
3. Run the model in a working e-commerce platform.
4. Analyze acquired data to explore the relationship between the variables corresponding cognitive biases, their visual execution and consumer behavior to provide conclusions and practical implications of the usage of cognitive biases and their visual execution in e-commerce platforms.
5. Critically evaluate possible points of improvement of conducted experiment and provide suggestions for further research on cognitive biases, their visual execution and effect they have on consumer behavior in e-commerce platforms.

Research Design

In order to collect data, which could afterwards be used to evaluate variable effects and relationships, the experiment will be conducted to test against the impacts of selected cognitive biases and their visual execution on consumer behavior in e-commerce platforms.

The model employed four behavioral cognitive biases that could be plugged into website: countdown effect, bandwagon effect, loss aversion and gain effect. What is more, three different visual elements were chosen to support the presentation of these: brown, green and red. Different combinations of chosen variables together with control group were presented to the visitors of e-commerce platform, while their behavior flow was observed by using four main dependent variables: time on page, pages per session, page value and conversions. Each of these will be explained in more detail later. The data from the experiment was recorded and used for further analysis.

Research Methodology

The paper can be divided into two parts: theoretical and empirical. In the first part, the analysis on the literature will be provided. The most important and meaningful behavioral biases will be chosen. Following that, theory analysis on visual means of communication in e-commerce and WEB platforms will be carried out. Once this is done, the possible setups of visual execution will be investigated and the best applicable ones will be chosen to include in the experiment.

Once the theory is analyzed and matrix model is populated, the experiment will be conducted to test for the best working combination and the applicability of it in general. Finally, the data analysis will be made and final conclusions will be provided.

Research Sequence

1. Finding and defining the main theoretical cornerstones
2. The experiment model creation and implementation on running e-commerce platform
3. Collection of data (running the experiment on the platform)
4. Analysis of collected quantitative data
5. Experiment results overview, practical implications
6. Conclusions, based on empirical research findings; suggestions for future research

1. Literature Review

1.1. Cognitive Biases and E-commerce. How these are related?

In quickly booming, big-data driven e-commerce business segment, the trends of optimizing user experience, segmenting target audiences, following every step of potential customer is now bigger than ever. What is more, various tools are used not only to provide exceptional experience for the client, but personalize the provided information, shape the content in a way, to influence consumer behavior, thus pushing the audiences toward completing business targeted goals (Alexander, 2006) (Allagui & Lamoine, 2008) (Wan, Menon, & Ramaprasad, 2009). Minimization of clicks and micro conversions to reach ultimate site goal has become a standard. Because of that, business owners, webmasters, advertisers and many other working with e-commerce platforms now are searching for new ways of improvement (Alexander, 2006).

Through vast amounts of various testing and practical exploration professionals in this particular e-commerce business field have started a new trend of conversion optimization – they target the mind of their customers to a whole no level – not only webmasters try to get the information they put online seen and read, but also they target thinking patterns of the people to push them towards pre-defined business goals, even before they start consciously think about it. These patterns are called cognitive biases (Wilke & Mata, 2012) (Tversky & Kahneman, 1974). And these are emerging with great speed and velocity. In this research the relationship between cognitive biases and consumer behavior in e-commerce platforms is explored from academic perspective.

Naturally, with increasing amounts of online activities and businesses the competition among the business owners and webmasters is increasing as well (Compass.co, 2015) (Alexander, 2006). The online industry possesses overwhelming pace: the speed in which the environment changes, the amount of possible experiments, the speed in which information is spread are very high, thus forcing webmasters, business owners and marketing professionals to constantly search for tools, that would guide potential clients through the cycle of customer lifetime as fast and as efficient as possible (Alexander, 2006) (Wan, Menon, & Ramaprasad, 2009). As a result, the increasing number of e-commerce websites is being equipped with various tools addressing these unconscious thinking patterns of the people, which could be called “heuristic thinking” (Tversky & Kahneman, 1974), and is activated by so called "cognitive biases" (Tversky & Kahneman, 1974). With time, these features are only getting better and more complex. If they are gaining popularity, maybe they are working?

However, despite the fact that there are many scholarly works on cognitive biases and consumer behavior in e-commerce platforms, there are no signs of researches unifying these two concepts. As it could be seen from current trends in practice, professionals in the online businesses are already making actions and tools, which could be considered a result of cross-interaction of these two major fields. In this literature review the theory on cognitive biases and consumer behavior in e-commerce platforms will be overviewed, thus examining and searching for possible points of interaction of these major academic fields.

The reviewed literature can be divided in two major groups:

- Cognitive Biases. The general researches will be overviewed. More focus will be shifted towards literature on following behavioral biases:
    - Loss aversion
    - Rhyme as a Reason
    - Bandwagon Effect
    - Countdown Effect
- Consumer behavior in e-commerce platforms:
    - Cognitive biases in action
    - Means of information provision
    - The ways of visual execution

The next segment of the paper discusses cognitive biases and possible application of these in e-commerce platforms in more detail.

1.2 Cognitive Biases

1.2.1 History of Cognitive Biases. The term itself was introduced by Amos Tversky and Daniel Kahneman in their paper “Judgement under Uncertainty: Heuristics and Biases“ in 1974. According to definition, cognitive biases are “systematic errors in judgement and decision-making, typical to all people, which can occur because of cognitive limitations, motivational facotrs, and/or adaptations to natural environments” (Wilke & Mata, 2012). In other words, cognitive biases describe “people’s systematic, but allegedly flawed patterns of responses to judgement and/or decision problems” (Wilke & Mata, 2012) (Tversky & Kahneman, 1974) (Kahneman & Tversky, 1982). The study by Tversky and Kahneman addressed the people’s decision making, taking into account they have limited rescources (information, time, etc.). The study examined how humans’ conclusions about surrounding world based on imperfect information (so called “bounded rationality principle” introduced by Herbert Simon (1955)) were affecting the judgement and/or decision making and what errors in some cases it may cause (Tversky & Kahneman, 1974) (Thaler, Tversky, Kahneman, & Schwartz, 1997). The findings of this research explained, that biases are the consequence of the use heuristics – simple cognitive principles, when decision or judgement is made relying on little information (Tversky & Kahneman, 1974) (Wilke & Mata, 2012). In such cases, when humans must use these “shortcuts” or “rules of thumb”, judgements of the people may depart substantially from normative standards (Haselton, Nettle, & Andrews, 2005) (Gigerezer & Selten, 2002). Tversky and Kahneman demonstrated this by using simple probability theory. People were asked to give the most likely coin-filp sequence out of three following: HTHTTH, HHHTTT or HHHHTH. Based on the responses, the first sequence was the most likely to happen. However, all three have equal mathematical probabilities of occurrence. This behaviour was called “gambler’s fallacy” by Tversky and Kahneman: the more bets are lost, the more the gambler feels, that win will occure, even though, each new turn is independent from the last one (Tversky & Kahneman, 1974).

1.2.2 Criticism of Cognitive Biases theory. Even though, the study on heuristics and biases by Tversky and Kahneman kick-started the research of the field, it also was and still is criticized. One of the most active critics of this theory is Greg Gigerenzer. First of all, the findings by Tversky and Kahneman are considered lacking statistical reasoning. Gigerenzer points out, that "practicing statisticians start by investigating the content of a problem, work out a set of assumptions, and, finally, build a statistical model based on these assumptions. The heuristics-and-biases program starts at the opposite end" (Gigerenzer, 1996). The second critique is that the nature of the bias study itself is confusing and the so-called cognitive fallacy is a result of additional context, which is provided during experiments, thus from this perspective, people's decisions still remains somewhat rational (Gigerenzer, 1991) (Gigerenzer, 1996) (Gigerenzer & Todd, 1999). The third point of critique is that demonstration of biases in the research of Tversky and Kahneman are built on comparison of people's responses versus statistical principle, without any amortization regarding context. In this way, the content and context of the behavioral problem remains unevaluated (Gigerenzer, 1991) (Gigerenzer, 1996). Taking these into account, critics conclude, that the heuristics-and-biases program is too vague to be considered as significant human behavior explanation. The fallacies in the experiment model make it questionable and falsifiable (Gigerenzer, 1993) (Gigerenzer, 1996) (Gigerenzer & David, 1987).

1.2.3 The Influence of Cognitive Biases on Behavioral Psychology. To summarize, there is no question, that the research on cognitive biases by Kahneman and Tversky opened a whole new chapter of behavioral psychology, however, the methods used are considered to be vague and in some cases even more confusing than clarifying (Gigerenzer, 1991) (Gigerenzer, 1996) (Gigerenzer & Todd, 1999). The main argument in this particular field is emerging not around the validity of the behavioral patterns (which are obviously present), but around means of measuring and explaining the reasoning behind the outcomes of human reactions (Kahneman & Tversky, 1996) (Gigerenzer, 1996) (Gigerenzer & Todd, Simple heuristics that make us smart, 1999). Initial research by Kahneman and Tversky, together with the critique by Gigerenzer et al. proves one focal point of cognitive biases assessment: the construction of provided information (sequence, context etc.) plays significant role in people's behavior (Gigerenzer, 1993) (Kahneman & Tversky, 1996) (Gigerenzer, 1996).

As mentioned earlier, the studies on cognitive biases are still being conducted. As for now, the total of around 80 different biases could be identified (Wilke & Mata, 2012). The emergence of new patterns is still happening, as researchers keep discovering new patterns, which could be classified as the ones triggering heuristics, thus classified under the field of cognitive biases. In the development of this field, three major classifications of cognitive biases emerged (Wilke & Mata, 2012) (Tversky & Kahneman, 1974) (Hardman, 2009):

- Decision making / Behavioral biases;
- Memory biases;
- Social biases.

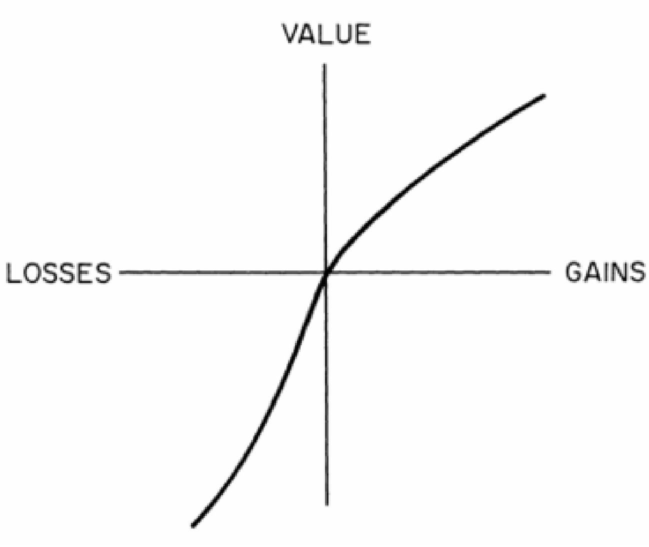
As this research focuses exclusively on consumer behavior online, so the main field of cognitive biases examined in this paper is the first one: decision making / behavioral biases.

1.2.5 Cognitive Biases and E-commerce Platforms. In the booming field of e-commerce businesses, big-data is the major progress driver. All steps, interactions, cursor hovers can be tracked, recorded and stored for further analysis. Owners of the businesses use this data to optimize their platforms. And for e-commerce platforms the ultimate goal is conversions. So, through lots of testing and experimenting with the e-commerce sites, the industry is moving towards more and more customer segmentation. The new content management tools enables to take personalization to a whole new levels – content can be changed and customized, to meet personal needs of almost every website visitor. This approach requires a lot of analysis, also, ability to predict and estimate the consumer's behavior, preferences, and needs. This big-data driven industry now is re-shaping the understanding of a customer itself: from rational approach to customer – providing required information, making sure that it is seen and read the industry moves to a bit different understanding. Industry moves to updated picture of the customer - a whole new emerging dimension is added: unconscious rationality, or so called and previously discussed bounded rationality (Alexander, 2006) (Allagui & Lamoine, 2008) (Wan, Menon, & Ramaprasad, 2009). With big-data, and advanced online technologies in action, complex models and tests could be run, thus targeting not only conscious rationality of customers, but also deeper level of understanding and decision making: cognitive biases. Because of naturally formed circumstances in the e-commerce business, many of the platforms are being equipped with tools, which stimulates thinking patterns in a way, very similar to what cognitive biases would (Wilke & Mata, 2012) (Wan, Menon, & Ramaprasad, 2009).

In the following part of the paper several cognitive biases will be discussed in more detail. These were picked according to possibilities of adaptation online, also theoretical background was provided, to better picture how particular tool, which could be used to alter consumer behavior online, is related to the concepts of cognitive biases theory.

1.2.6 Loss Aversion. Being one of the most popular cognitive biases' loss aversion bias was first discussed and demonstrated by Tversky and Kahneman (1991). The theory basically states, that people are more willing to avoid losses than acquire gains. Authors claim, that gradual increase in gains result in less marginal returns in value, than gradual decrease in losses (Figure 1).

Figure 1. An Illustration of a Value Function (Tversky & Kahneman, 1991)



Tversky and Kahneman built their empirical research on series of experiments made by Kahneman, Knetsch and Thaler (1990). The researchers conducted a series of experiments in a classroom setting. The participants were given decorated mugs, with a retail value of around $5. Then, the participants were split into two groups: sellers and choosers. Each individual from sellers group were given the mugs, stating, that even though they are now owners of the mugs, they have an option of selling their possession and were asked to mark, at which price they would sell their mug. Choosers group were not given the mugs, but were simply asked to provide the price, at which they would buy a mug from their classmate. The median value of the mug for sellers group was around $7 and $3.5 for choosers. Authors conclude, that the difference of these values reflects one of the most important features of loss aversion bias - *endowment effect*, which states that loss of the utility is greater when in the need of giving up the valued good, compared to the utility acquired with receiving it (Tversky & Kahneman, 1991) (Kahneman, Knetsch, & Thaler, 1990) (Plott & Zeiler, 2005).

In the context of online businesses, this cognitive bias could be used by providing information of what could potential customer be losing without the product / service. By familiarizing oneself with the provided product / service, subject will start to see potential losses of not owning it. What is more, future money, that one could save from not purchasing product / service, will not appear as valuable as the given item or service package (Tversky & Kahneman, 1974) (Jennings, 2000) (Allagui & Lamoine, 2008).

Interestingly, scholars did not yet differentiated the most effective mean of communication to stimulate loss aversion bias. One of the ways to do that is creation of previously discussed endowment effect, also this outcome can be reached from different approach: statement stressing possible gain of making decision now and possible loss of not making it can be constructed alternatively (Tversky & Kahneman, 1974) (Plott & Zeiler, 2005) (Bateman, Kahneman, Munro, Starmer, & Sudgen, 2003), in terms of this particular research, the balance has to be created in order to measure this bias effectively. The construction of such statement is very similar to the previously discussed loss aversion statement; however instead of creating endowment effect and stressing potential loss in the future, possible gains of making decision now versus potential loss in the future should be stressed (Tversky & Kahneman, 1974) (Bateman, Kahneman, Munro, Starmer, & Sudgen, 2003) (Camerer & Loewenstein, 2004) (Haselton, Nettle, & Andrews, 2005).

1.2.7 Rhyme as a Reason. The theory behind this cognitive bias states that statement is perceived to be more truthful when it is presented rhymed (McGlone & Tofighbakhsh, 2000): the rhythmic, rhymed phrases are naturally more fluent, thus they are better understood by people and judged more positively. This effect suggest that attractive lexical activation builds more trust and naturally makes subjects accept the statement easier (Meyer, Schvaneveldt, & Ruddy, 1975) (Hillinger, 1980) (Reber, Winkielman, & Schwarz, 1998). McGlone and Tofighbakhsh (2000) performed an experiment on undergraduate students, to test against the perception of rhymed statements and the people’s willingness to perceive such statements as more trustworthy. The subjects were provided with several rhymed aphorisms and paraphrased versions of these that do not rhyme. The outcome of the research showed, that participants perceived rhymed aphorisms as more accurate and trustworthy. What is more, McGlone and Tofighbakhsh states, that this may apply not only to aphorisms, but to much broader spectrum. As an example, the famous O.J. Simpson's trial could be taken. Attorney Johnnie Cohran made a plea which was following: "If the gloves don't fit, you must acquit!" This created a major buzz in media, thus increased the likelihood of trial rehearse (Buckley, 1997). The rhymed statement was fluent and attractive, thus not only brought more attention to the issue, but made it look more reasonable (McGlone & Tofighbakhsh, 2000). Just imagine what could have happened if Johnnie Cohran would have said some blunt statement?

In terms of marketing in general, sometimes this bias is used to stimulate previously described effects. Companies use rhymed brand supporting slogans, try to use some rhymes in their commercials etc. However, online marketing, and e-commerce sites are no exception – rhymed product descriptions, the same slogans, or supporting online materials are sometimes used by online businesses.

1.2.8 Bandwagon Effect. This cognitive bias is usually considered a cultural phenomenon too. According to definition, bandwagon effect is the act when the rate of adopting ideas, trends, beliefs, etc., increases when it is already undertaken by others. In other words, the probability of individual acquiring the idea or belief is positively related with the number of other individuals who already have done the same thing (Colman, 2003). This phenomenon can be spotted and used in various different fields, but the most important is politics and economics. In order to keep this paper as accurate as possible, more focus will be shifted towards the latter. In this field, bandwagon effect is described as set of interaction of demand and preference (Leibenstein, 1950). The author claims that because of this cognitive bias, normal supply and demand curve (which explains buying decisions of individuals only on price and consumer preference) can be distorted from its normal state. This fact can also be closely related to marketing, because through marketing activities the economy and the market can be stimulated, thus bandwagon effect could emerge into decisive power and actually lift the normal demand curve upwards. In other words, through stimulating bandwagon cognitive bias, the demand of the product or service can be significantly increased (Gisser, McClure, Okren, & Santoni, 2009).

1.2.9 Countdown Effect. Theoretically, countdown effect is not separate cognitive bias per se. The countdown effect could be more accurately defined as broadly used concept, which employs several features of other behavioral biases. Firstly, countdown effect stimulates some sort of loss aversion cognitive bias (Tversky & Kahneman, 1974) (Oechssler, Roider, & Schmitz, 2009): the statement followed by countdown creates effect of scarcity. In other words subject is presented by dilemma: either the opportunity is taken or lost. In such cases, heuristic thinking may come into place and push individual towards positive decision (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991) (Reddi & Carpenter, 2000). At this point we may get back to previously pictured Loss Aversion utility function (Figure 1). By definition of the theory, humans by default value the pain of losing something much more than utility of acquiring something. So in such case, subject is willing to take risk, just to avoid the possible pain of not taking the opportunity (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991). Ultimately, the combination of loss aversion and pointing out the fact of limited offer possesses a great power in evoking heuristic thinking.

1.3 Visual Execution Importance for Consumer Behavior in E-commerce Platforms

With the number of e-commerce platforms increasing, the fight for the customers is getting more and harder. In the times of Big Data, customer behavior can be analyzed to almost tiniest pieces. Through various testing, data and customer behavior analysis webmasters and marketers have started to address the specific patterns of human behavior and thinking. Surprisingly enough, these patterns are very similar to the concept firstly defined by Tversky

& Kahneman (1974) by the name of cognitive biases. However, in literature regarding e-commerce and WEB platforms in general, “electronic decision aids / tools” is more common term (Wan, Menon, & Ramaprasad, 2009). The most interesting part about this concept is that good portion of academic literature agrees, that online shoppers can be provided with specific information, which would expand their bounded rationality (already discussed by Tversky, Kahneman and others) to make quality decisions and (hopefully) convert more and faster (Wan, Menon, & Ramaprasad, 2009) (Simon, 1955). According to various researches, people are likely to follow the path which is the easiest (Payne, Bettman, & Johnson, 1993) (Todd & Benbasat, 1999). What is more, with increasing information flows (and this is exactly what is happening at the moment in e-commerce field) individuals tend to rely on their heuristics driven decisions (Todd & Benbasat, 1999) (Tversky & Kahneman, 1974). So in this situation, tools addressing cognitive biases are extremely useful for both parties: e-commerce clients and owners. It can be already seen, that by the means of various tools and strategies the consumer behavior in e-commerce platforms can be influenced. What is more, in this particular market segment competition is as high as ever at the moment and it is only increasing.

For businesses it is getting more and more difficult to attract, engage and, ultimately, convert their customers and visitors (Wan, Menon, & Ramaprasad, 2009). Not so long ago, WEB platforms, e-commerce websites did not had much competition and were able to simply dictate their rules and count on customers to adopt to the way they are providing information and building their sites. However, now the situation changed dramatically: client is the king and companies are doing everything to be attractive to their visitors. Starting with designs, finishing with technical site execution and various conversion optimizations the one and only target for the web site owners and developers is to make customer experience as good as possible, to provide for him/her as much as possible, but only the information that is needed at particular stage of customer journey (Jennings, 2000) (Rohrbeck, Steinhoff, & Perder, 2010) (Alexander, 2006) (McMullen, Hawick, Du Preez, & Pearce, 2012). In this research, the major focus is very specific kind of WEB platforms – e-commerce sites. In this field, the ultimate goal is the conversions. As discussed previously, to achieve that, various different tools and strategies are being employed. The e-commerce business owners, marketing managers and everybody else in this business are now focusing on conversion optimization: providing the people with information at the right time, in the right place (Alexander, 2006) (Biers & Richards, 2005) (Compass.co, 2015). However, one of the various e-commerce platform features is gaining more and more importance. It is visual execution. The industry now experiences increase of traffic from various different sources and devices, and to look appealing every time is crucial. By not making content and features visually appealing, businesses are risking to simply lose visibility (Wan, Menon, & Ramaprasad, 2009) (Allagui & Lamoine, 2008). We can narrow down this movement of WEB sites' visual execution optimization to simple cornerstone features: these are colors (Alexander, 2006) (Allagui & Lamoine, 2008) (Cebi, 2013).

In the case of this research, it is highly important not to overlook options and possible setups for cognitive biases visual representation, because only providing information that should trigger person's heuristic patterns of thinking is simply not sufficient enough. Properties and means of visual representation must be explored and applied, to ensure that information is seen and received.

1.3.1 Cognitive Biases' Visual Representation Online.

Having previously reviewed literature and concepts in mind, several statements can already be made: theoretically the adoption of cognitive biases on e-commerce platforms might bring additional value to both customers and business owners. However, the means of visual representation of the biases' triggering features has to be well thought out. Previously, the cognitive biases that could be the most effectively implemented online were discussed, but to effectively use these features that they provide, the optimal visual execution must be chosen. In the previous chapter, the importance of visual execution was discussed. What is more, the concept was narrowed down to the key-feature of visual content representation online, which is color (Alexander, 2006) (Allagui & Lamoine, 2008) (Cebi, 2013). According to Jennings et al. (2000), visual execution (color in this research case) has to be appealing and attractive, so that it not only would make information visible, but also easily understandable for the customer. Theoretically, these color properties could possibly increase the possible effectiveness of employed features of cognitive biases. As the content part is more or less pre-decided by specific phrase formulation which enables heuristic thinking, the other part of visual execution should be constructed after detailed analysis on different colors' effect on e-commerce platforms.

In order to display biases understandably for the consumer online and enable them to trigger bounded rationality behavior of the potential customer, colors should stimulate information perception mechanisms (e.g. highlighting the text, which would catch subject's attention. Once the information is seen it is being read, and once it is read, the heuristic thinking is activated, thus putting cognitive bias into action) (Wilke & Mata, 2012) (Camerer & Loewenstein, 2004) (Webb & MacMillan, 1995). In e-commerce platforms (especially now), visual execution is important as much as content itself is. (George, 2004) (Alexander, 2006) (Pellet & Papadopoulou, 2009) (Wan, Menon, & Ramaprasad, 2009).

So, if the text formulation and specific phrases triggering cognitive biases could be taken form the researches by Tversky and Kahneman and plugged in to represent the content part in e-commerce platform, further exploration on visual execution has to be conducted. After analysis on what behavioral properties different colors stimulate and why, at least two of them (possessing different stimulating properties) should be chosen to equip the cognitive bias with. The properties of different colors are discussed in the following segment of the paper.

1.3.2 The Ways of Visual Execution. In terms of this research and e-commerce platforms, visual execution could be split into two segments: design and colors. As usually, designs of the sites are constantly being developed by webmasters and is long run process aiming at optimizing the user experience and functional flow of the website (Alexander, 2006) (Allagui & Lamoine, 2008) (Wan, Menon, & Ramaprasad, 2009). What is more, it is already proven, that colors are important factors in stimulating person's mood, information perception features, interface favorability and it even can be one of the main features to increase the time spent on e-commerce sites by the consumers (Lichtlé, 2007) (Allagui & Lamoine, 2008). Various different colors and their properties (such as hue, brightness, saturation etc.) can stimulate different behavior (Pellet & Papadopoulou, 2009). Bright, intensive colors increase awareness, brings more focus and are more aggressive, however counterparts of such colors are bringing totally different results in customer behavior (Jennings, 2000) (Pellet & Papadopoulou, 2009). What is more, not only colors are playing big part in visual execution. The overall design, location and information provision timing are playing very important roles (George, 2004) (Alexander, 2006) (Wan, Menon, & Ramaprasad, 2009). So not only the colors and design should be considered, but also the time on location at which the information is provided should be taken in to account, when the consumer behavior in e-commerce platform is under attempt to be influenced. In the case of this research, the placement of the cognitive bias triggering content is clear – the step before the goal completion, so that heuristic thinking of a customer would be triggered and final decision of purchase would be made as fast as possible. To continue with, statistically thinking, in order to get the best results, the bias should be placed at the step where consumer retention is the highest – in other words, where the webmaster, business owner or marketer wants to push subject to make decision which satisfies business goals the most.

Color properties in visual advertising, thus in the field of e-commerce too, could be split in three components: hue, saturation and lightness (Lichtlé, 2007). What is more, based on the research made by Lichtlé (2007) it can be stated, that color undeniably plays a high role in advertising and information perception. It can evoke specific feelings of preference and stimulate alertness. These are two options which are needed for cognitive biases to be equipped in e-commerce platforms, so that the corresponding information could be percieved and would trigger heuristic thinking of a potential customer. However, various researches show, that even though color undeniably has affect on people and their perception of information, same colors might affect different people in different ways (Lichtlé, 2007) (Wan, Menon, & Ramaprasad, 2009) (Allagui & Lamoine, 2008).

However, even though preferences for the single colors may differ among people, some researches show, that individuals have strong preferences towards liking some color combinations (Palmer & Schloss, 2012). The general understanding of the color could be sliced to three simple dimensions: hue, saturation and the level of brightness (Palmer & Schloss, 2012). Researches showed, that people in general tend to prioritize bright colors with high saturation (Palmer & Schloss, 2012) (Biers & Richards, 2005) (Lichtlé, 2007).

Yet another interesting point regarding color preferences is that they differ among adults and infants (Palmer & Schloss, 2012), however main point of interest in this research are adult subjects, so the preffered color setups by adults will be taken into account in the future.

To continue with, the context in which color and/or color combinations are presented also matters. Colors can can evoke specific emotions, thus the ones representing favourable emotions may be prioritized (Palmer & Schloss, 2012) (Lichtlé, 2007).

Another approach to color prefference reasoning could be explained by natural evolution. Historically, the specific colors helped our ancestors to navigate and for example identify potential dangers (Humphrey, 1976). The colors could and still is sending specific messages in the nature: color of a flower attracts a bee, color of a fruit grabs an attention of a bird which later will spread the seeds of a plant (Humphrey, 1976). By the time our ancestors started to play a role in prehistoric ecosystem the whole nature was most probably full of various colors, each of which had a specific message to transmit (Humphrey, 1976). It is higlhy likely, that in the past the color played a big part for our ancestors in understanding the nature, environment and even helping them to survive (Humphrey, 1976). However, it is highly likely, that nowadays colors do not play such crucial role as they used to in prehistoric times: babies are given toys which usually are coloured in many different colors, but not different in any other means (Humphrey, 1976). But the so-called genetic memory, a result of many years of evolution is much more powerful than the things baby learns as he or she grows up: various studies on primates and humans showed, that a lot of significance is being attached for the red color for example (Humphrey, 1976) (Daugherty, Li, & Biocca, 2005) (Wan, Menon, & Ramaprasad, 2009). Historically, red was and still is a most common signal of danger in the nature (Humphrey, 1976). Red contrasts very well with dominant colors that could be found in the nature (green, blue, yellow). What is more, red is the color of blood. Throughout many years of evolution this was used and percieved as a warning signal (Humphrey, 1976).

Getting back to more recent times, red color still have effect on humans: during various experiments it was found out, that exposure to this color may increase blood pressure of individuals, increase alertness, helps to focus the sight on specific points (Biers & Richards, 2005) (Lichtlé, 2007) (Palmer & Schloss, 2012).

So, in terms of marketing and visual appearance online – what colors should be adopted in order to have the best effect on performance? Nowadays, it is argued that color prefferences are shaped on cross-cultural levels (Aslam, 2006). The sholars write, that color was and still is important element of marketing communication, which greatly influences how customer perceive service or product, what is natural consumer behaviour etc. What is more, in some cases companies had failed just because of inappropriate use of colours (Ricks, 1983). The research by Aslam (2006) points out several important things: “the meanings given to some colours may be pancultural, some regional and some unique to specific cultures”.

In case of this research, several different setups of colors had to be prepared, in order to find the best performing one, taking into account that various external factors may affect the color perception. It was decided to adopt colors, which are very natural and deeply emedded into evolutional code of human beings. To satisfy this condition, the following colors were chosen to form combination groups with cognitive biases:

- Red – stimulates alertness, increases awareness. In some researches subjects stimulated by this color recorded increased attention and blood pressure levels (Lichtlé, 2007) (Allagui & Lamoine, 2008) (McMullen, Hawick, Du Preez, & Pearce, 2012)
- Green – has calming effect, may potentially increase awareness, as it considered not being that stressful. Researches in some cases recorded, that individuals were able to spot specific details and/or features better when presented with calming set-up of color features (Lichtlé, 2007) (Allagui & Lamoine, 2008) (McMullen, Hawick, Du Preez, & Pearce, 2012).

1.4 Cognitive Biases' usage in E-commerce Platforms: Shaping the Consumer Behavior Online

To generalize, cognitive biases are already being assessed in e-commerce platforms (Wan, Menon, & Ramaprasad, 2009). The researchers examining consumer behavior online took one more step forward from cognitive biases and designed concept of "electronic decision aids/tools" which are serving for same purpose as cognitive biases do in cases described by Tversky, Kahneman and others.

According to the literature in this field, the attention to cognitive biases and heuristic thinking in online platforms was brought naturally by increasing competition in business to client market segment and also by search engine marketing gaining more and more popularity and influence (Wan, Menon, & Ramaprasad, 2009) (Haubl & Murray, 2003) (Olson & Widing, 2002).

With e-commerce platforms on the rise webmasters, marketers and business owners are enabled to provide not only major product listings, but also increase the information value that it is provided to potential customer (Wan, Menon, & Ramaprasad, 2009). Theoretically, more information provided to a subject will help to increase the confidence in the judgement about product or service, will help to better match their needs and preferences and finally will result in more knowledge about the item they are examining (Ariely, 2000). However, increasing amount of information and/or data is positively correlating with the amount of attention required by the subjects. In other words, the attention must be caught and kept throughout the whole customer journey, ensuring that all the data and information is received (Ariely, 2000). Only then, positive outcomes of additional information provision can be expected (Ariely, 2000) (Wan, Menon, & Ramaprasad, 2009).

Here is where so-called electronic decision tools come into place: theoretically, such tools can help subjects (online shoppers in this particular case) to make decisions faster (despite the increased amount of information, which should be processed in regular way) by expanding subject's bounded rationality (Wan, Menon, & Ramaprasad, 2009) (Wilke & Mata, 2012) (Gigerenzer, 1993). In reality, however, these decision tools may access even deeper patterns of thinking – heuristics, thus activating different level of rationality (Kahneman & Tversky, 1982) (George, 2004).

Whereas increasing amounts of information is one side of online consumer struggle, there is also other part of the internet phenomena that brings back the concept of Herbert Simon's "Bounded rationality" (Simon, 1955). Together with increase of information and data, the numbers of products and services online are also increasing. Together with overwhelming amounts of possible choices humans are faced with "a mental state in which the amount of choice information that needs to be processed exceeds the committed cognitive capacity of the decision-maker" (Simon, 1955). In other words, the amount of possible decision and information is so big, that it becomes impossible to process everything, thus decision maker cannot make a fully rational decision and has to rely on bounded rationality thinking.

Having this in mind, it can already be seen – first of all, it becomes impossible for human brain to process vast amounts of information in order to make rational decision online (Haubl & Murray, 2003) (Wan, Menon, & Ramaprasad, 2009). Because of that the behavior of subjects happens to be irrational sometimes (Simon, 1955) (Tversky & Kahneman, 1974). What is more, creating additional sense of urgency may result in even less time for consideration and faster action (Tversky & Kahneman, 1974). This is where countdown in online e-commerce platforms comes into place. Several different heuristic thinking patterns can be triggered in following setup: first of all, possibility of making rational choice is already low, because of high volumes of information flow and possible choices (Wan, Menon, & Ramaprasad, 2009). What is more, presented with such setup, humans are willing to commit and make positive decision (in other words – to agree and/or say “yes”), because of heuristic thinking patterns (Simon, 1955) (Tversky & Kahneman, 1974) (Gigerenzer & David, 1987). Therefore, urgency that is created with additional countdown on e-commerce platform increase the effects of previously mentioned factors (Simon, 1955).

Finally, looking from technical perspective, the implementation of countdown tools in e-commerce platforms is rather easy. What is more, there are several pre – built tools for webmaster use. All these factors together, make countdown effect one of the most popular cognitive bias assessment tool online.

1.5 Conclusion

To summarize with, this research is trying to build a bridge between two major movements in academia: behavioral cognitive biases theory, which could be classified under classic psychology and human behavior studies, and newly emerging set of studies on internet, WEB sites and e-commerce platforms and their performance optimization. The possible inter-relation between these two fields can be clearly noticed; however there is no clear research on the two of these fields and possible properties of their interaction. From the practical side of these fields, it can also be seen from current trends in internet industry, that customers are getting more and pickier. Because of that, WEB developers and marketers are forced to improve constantly: to provide information in the right way, at the right time in the right place. What is more, to achieve their business goals, e-commerce players are using more and more tools, to not only provide for the customer, but to push him/her to make final decision as fast as possible. The major industry players are already testing various solutions, that could be potentially targeting heuristic level of consumer thinking and behavioral cognitive biases may be being plugged into action. However, there is no literature or experiments examining the theoretical feasibility of such tools on consumer behavior. Having this in mind, the main research question of this research emerges: how do cognitive biases (taking into account their visual execution) that influence decision making affects the performance of e-commerce platforms

2. Research Methodology

As it can be already noticeable, this research consists of two major segments: cognitive biases (and their visual execution) and consumer behavior. The first segment consists of a set of independent variables and the second one contains a collection of dependent variables, all of which will be discussed in this part of research. Also, detailed variables of which each segment consists will be presented, together with reasoning behind.

To continue with, in this part of the paper the theoretical framework and research problem will be explained in detail and plugged into research model. Since theoretical ties between cognitive biases (together with their visual execution) and consumer behavior in e-commerce platforms could be tied it is critical to test empirically the initial hypothesis: whether addressing cognitive biases equipped with specific visual execution can influence consumer behavior. It is crucial to test, if these setups could be used to stimulate pre-defined e-commerce goals.

Out of this, the main goal of the research emerges – to examine is the relationship between usage of cognitive biases (taking into account their visual execution) and consumer behavior in e-commerce platforms. To test against that, it was chosen to conduct an experiment on a running site.

To add up, answering research question - how cognitive biases and their visual execution affects consumer behavior in e-commerce platforms, required in-depth analysis of the data, acquired during the experiment. In this part of the paper, the means of analysis are overviewed as well as the setup of the experiment itself. Because of that, this section of the paper could be divided into following parts: research design, setting and participants, instrumentation, ethical considerations and weaknesses and limitations of the research model.

There are numerous researches done on both cognitive biases and consumer behavior in e-commerce platforms. The concept of cognitive biases is still being discussed very heavily: whether it is significant enough to build behavioral theories, should it be considered as worthy concept examining decision making, etc. (Gigerenzer, 1996) (Gigerenzer, 1993) (Gigerenzer & David, 1987). With the emergence of e-commerce platforms the consumer behavior is being studied more than ever. What is more, the access to overwhelming amounts of data lets segment customers more and more, and because of that, the individual rationality of a person is being addressed less. Instead, tools that could be classified as means of targeting cognitive decision making biases are used more and more (Alexander, 2006) (Allagui & Lamoine, 2008) (Wan, Menon, & Ramaprasad, 2009). However, there are no significant researches conducted on the linkage of these two: cognitive biases and consumer behavior in e-commerce, even tough, as discussed in the literature review of this paper, some tools are emerging and being used in e-commerce business, that could be classified as addressing cognitive biases.

2.1 Research Problem

This paper is nothing more than the attempt to fill in this gap between cognitive biases' theory and consumer behavior in e-commerce platforms. To accomplish that, the following research question was constructed: how cognitive biases and their visual execution affect consumer behavior in e-commerce platforms?

2.2 Research Model

The experimental strategy was chosen to be conducted. Since main point of interest of this research is cognitive biases, it is merely impossible to test this concept in any other setting. Since the subjects may not answer the questionnaires objectively, the one and only indicator of cognitive biases effects is the real human behavior when exposed to these specific messages triggering biases. What is more, experimental setting helps to examine causal relationships and effects in the real and live setting (Malhorta, 2010).

In this particular case an experimental design will help to critically evaluate site performance with and without cognitive biases in action, as well as the impacts of visual execution of these. Collected data will be used to perform quantitative data analysis and results will be used to test against hypotheses.

Investigation will be carried out in order to evaluate how people will react to stimuli generated by cognitive biases and their visual execution. Previously numerous experiments were carried out on focus groups of people (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991) (Thaler, Tversky, Kahneman, & Schwartz, 1997), thus provided controversial results. The main challenge of this experiment will be to work out a setting addressing cognitive biases and heuristic thinking of the subjects.

After the in-depth literature review on the two big fields: behavioral cognitive biases and consumer behavior in e-commerce platforms, the research model for exploration of these fields interaction was constructed:

Table 1. The experiment model matrix

Cognitive Bias	**Visual Execution**	
	Red	**Green**
Countdown Effect	Countdown message, Page Title and Call to Action button in red	Countdown message, Page Title and Call to Action button in green
Bandwagon Effect	Bandwagon message, Page Title and Call to Action button in red	Bandwagon message, Page Title and Call to Action button in green
Loss Aversion	Loss Aversion message, Page Title and Call to Action button in red	Loss Aversion message, Page Title and Call to Action button in green
Gain Effect	Gain Effect message, Page Title and Call to Action button in red	Gain Effect message, Page Title and Call to Action button in green
Control	No message addressing cognitive biases. Page Title and Call to Action button in dark brown (matching general site style)	

From the matrix it can be seen, that theoretically, different cognitive biases setups together with specific visual execution should result in different consumer behavior (outcomes). The screenshots with actual pages of the site from the experiment can be found in Appendix 1. To better understand the logic behind the model itself, each segment with subcategories will be discussed in the following part of the paper.

2.2.3 The Choice of Cognitive Biases. As literature review revealed, there are various fields in which cognitive biases can be grouped (Tversky & Kahneman, 1974). The raw number of biases is more than 80, what is more, new ones are being registered too (Wilke & Mata, 2012). To critically assess the impact of these on consumer behavior in e-commerce platforms, several biases had to be selected out of many. In order to pick the most suitable ones, following the simple logic - biases should be compliant with following concepts:

- Addressing decision making. In this research main focus is consumer behavior and from e-commerce platform owner/administrator perspective the main goal is to stimulate customers‘ decision making. Thus biases used in the experiment must have been chosen in a way that the difference that they make (if any) could be visible in the short run. Because of that it was decided to focus on the cognitive biases, that affect decision making.
- Implementation possibility. Nevertheless chosen biases should have been addressing decision making, but they should have been possible to implement in e-commerce platforms in a manner understandable for very possible customer/visitor.
- Strength of validity. It was extremely important to pick only these biases, which are the most reliable and considered to be tested and proven to work.

Having set these three factors, it became possible to sort out the significant number of cognitive biases to acceptable number. The selected ones were these:

- Countdown Effect. In terms of this research it was timer, counting time until the end of the offer. It was proven by various researches, that this stimulates heuristic thinking of people and in such cases, subjects were willing to make positive decision (for example, say yes or agree with the provided statements) (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991).

- Bandwagon Effect. Another one proven to be working and widely discussed bias. From theoretic perspective it could be explained, that individuals perceive decision more trustworthy if it was previously made by a number of other people. The behavioral patterns of human thinking assigns amount of credibility directly proportional to the decision popularity among other subjects, taking into account the decision made by majority may not be the best one in the case of individual making decision (Tversky & Kahneman, 1974) (Leibenstein, 1950). In this research this cognitive bias was addressed by displaying the number of people that have already used the offer.
- Loss Aversion. Together with previous two ranks among the oldest and the most credible cognitive biases. As discussed in literature review, majority of people are trying to avoid any potential losses in the present, even though the potential gains in the future would be greater than losses. In other words, people are more willing to avoid losses than to acquire gains (Tversky & Kahneman, 1991) (Tversky & Kahneman, 1974). In this research, this cognitive bias was addressed by equipping the e-commerce platform with information, what a potential customer could lose if the offer ends up not used by the subject.
- Gain Effect. It is the second clause in testing subject’s loss aversion perception. Even though the theory behind gain versus loss (gain effect) and loss aversion is very similar (Tversky & Kahneman, 1991) (Tversky & Kahneman, 1974), but the approaches to these cognitive biases in terms of experiments can be different (Tversky & Kahneman, 1991) (Tversky & Kahneman, 1974) (Kahneman, Knetsch, & Thaler, 1990). Gain effect states, that once the image of the potential gain is created, the subject will be willing to value hypothetical gain more and will already imagine that offer rejection will result in his or her loss (Tversky & Kahneman, 1991) (Tversky &

Kahneman, 1974) (Kahneman, Knetsch, & Thaler, 1990). In order to test against this bias, additional statement has to be constructed, since both ways proved to be effective on people groups with previous tests carried out by scholars (Tversky & Kahneman, 1991) (Tversky & Kahneman, 1974) (Kahneman, Knetsch, & Thaler, 1990). In this research, the bias was executed by equipping the site with the message stating that subject has already some valuable feature reserved for him or her, thus creating some hypothetical value.

These were the main cognitive biases that were chosen to plug into experiment. However, this is only one part of the experiment matrix. The second one is visual execution.

2.3.4 Visual Execution. What? How? Why? Previously it was already discussed, that among various different means of visual execution the factor of colors was chosen. Of course, bad visual appearance may consist of many more design features far beyond simple color setup (Alexander, 2006) (Allagui & Lamoine, 2008) (Biers & Richards, 2005). Numerous variables could be classified as the ones reflecting visual execution (Alexander, 2006) (Allagui & Lamoine, 2008) (Daugherty, Li, & Biocca, 2005) (Allagui & Lamoine, 2008). Since employing several means of visual execution might make it difficult to measure separate factor influence on overall outcomes and experiment itself was being conducted on working e-commerce platform the main mean of visual execution was chosen: colors. According to the literature in this field, colors in e-commerce platforms can stimulate two different reactions: alertiveness and calmness (Jennings, 2000) (Allagui & Lamoine, 2008). In order to represent each of the possible reactions two extreme colors were chosen:

- Red – to stimulate alertiveness (Pellet & Papadopoulou, 2009) (McMullen, Hawick, Du Preez, & Pearce, 2012).
- Green – to create “calming” environment (Pellet & Papadopoulou, 2009) (McMullen, Hawick, Du Preez, & Pearce, 2012).

In the experiment, these color setups were executed by designing designated product pop-up windows, with different color dominance.

With this second part of the experiment in place, this research makes an assumption, that behavioral cognitive biases, provided with supporting visual aids can influence consumer behavior to accomplish specific goals targeted by e-commerce platform owners/administrators.

2.4. Research Question and Hypotheses

The ultimate question of this research is: how cognitive biases and their visual execution affect consumer behavior in e-commerce platforms.

Consequently, specific messages triggering cognitive biases and heuristic thinking together with their visual execution will represent the independent variables in this research. During the course of experiment several messages will be constructed to correspond different cognitive biases also, several visual execution setups will be prepared and finally each of these will be combined and put to randomly rotate on e-commerce platform. To continue with, consumer behavior will be tracked. In terms of this experiment, it consists of several dependent variables: page views, view time (time on page), page value (generated revenue from the page) and conversions (amount of conversions made). Combination of these represents overall consumer behavior properties: consumer engagement (page views, view time) and willingness to make a positive decision – convert (page value, conversions).

To answer the research question and examine what relationship cognitive biases and their visual setup configurations has on consumer behavior, following research hypotheses were formed:

Table 2. Hypotheses List

Hypothesis	Description
H1: Usage of Cognitive Bias will have a positive effect on conversion rate.	Presence of cognitive bias will increase the number of conversions within the tested group.
H2: Cognitive Bias will have a positive effect on customer engagement.	Presence of cognitive bias will increase viewed pages' number together with page view time.
H3: Cognitive Bias will have a positive effect on revenue generation.	Presence of cognitive bias will increase revenue generated during session on website (will generate higher page value).
H4: Countdown effect will have the biggest effect on dependent variables other cognitive biases that were put on experiment.	Since countdown variations are already widely used in e-commerce platforms, assumption is made, that it should give the biggest positive effects on sites.
H5: Cognitive biases with red color visual execution will have the biggest positive effect on dependent variables in comparison to the same biases with green color visual execution.	According to its stimulating properties, red color should increase the positive effects of cognitive biases on dependent variables

To summarize hypotheses, according to the literature in the field, the assessment of cognitive biases will have positive effect on consumer behavior. In this particular research case it should increase conversion rate, boost customer engagement and increase revenue generated by the e-commerce platform. The reasoning behind this logic follows the main theory of cognitive biases and heuristic thinking: triggering specific thinking patterns should push subjects to make positive decision (make a purchase), also, the assessment of cognitive biases in visually appealing way should result in increased engagement with the platform (subjects should be willing to consume the site content more, thus spend more time on pages and view more of them in general).

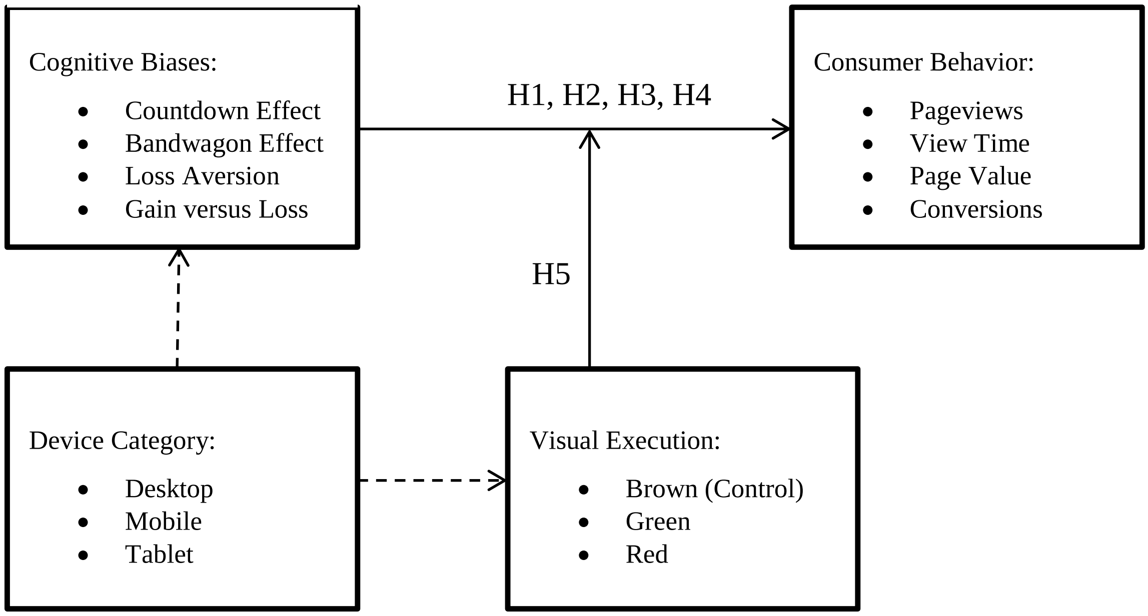
To continue with, countdown effect cognitive bias is one of the most widely used tool currently. The assumption is made, that the effectiveness of this bias is the reason behind the wide spread of it among the webmasters, despite there is no academic proof that countdown cognitive bias is the most effective of all.

Additionally, according to literature on visual execution and more particularly – colors, the final hypothesis is formed. Theoretically, red color has required properties that could stimulate the most efficient information perception, thus cognitive biases equipped with this color should be visible and perceived the best, therefore providing the most influence to the consumer behavior in e-commerce platforms.

Finally, the site on which experiment was performed is optimized only with desktop devices. Mobile and tablet platforms might not represent the independent variables of the experiment (cognitive biases and their visual execution) as expected, thus effecting the performance of dependent variables.

In order to explain hypotheses and their interaction better the following graph was constructed:

Figure 2. Hypotheses Visualisation



Each variable, the reasoning behind the construction of these is explained in the following chapters.

2.5 Research Instrumentation

Research instrumentation of this paper could be divided into two major segments: experiment and collected data analysis.

In order to better explain experiment structure (which was provided previously on Table 1) and logic behind, the following variable table was constructed:

Table 3. Variables' List

Name of Variable	Type of Variable	Description
Cognitive Bias	Nominal - Independent	Each cognitive bias was coded as follows: 0. Control Group – no cognitive bias 1. Countdown Effect 2. Bandwagon Effect 3. Loss Aversion 4. Gain Effect
Color	Nominal - Independent	Each page variation had three possible color variations: 0. Brown (matching site style – was used only for control group) 1. Red 2. Green
Pageviews	Scale - Dependent	As the interactions were recorded on session level, many page views could happen during one visit. The more pages are viewed by unique visitor – the higher the engagement rate with the site is.
View Time	Scale - Dependent	Similarly, the more time subject spends on single page – the more content is being consumed, thus meaning better engagement with the site.
Page Value	Scale - Dependent	The value of the conversion (if any). Thus the higher the Page Value, the more revenue was

		generated with the conversion.
Conversions	Dichotomous - Dependent	True/False variable coded with 0, 1 values to signal in which cases the purchase was made during given session on website. The higher the number of the conversions in the given group of subjects, the better conversion rate.
Device Category	Covariate	The website, on which the experiment was run, can be accessed by various types of devices (desktop, tablet, mobile). Each device category was coded in following way: 1. Desktop Device 2. Tablet Device 3. Mobile Device This variable is very important in testing group performance, since the website on which the experiment was run was optimized for desktop devices only.

As mentioned before, the first step of the experimental study was creating an experiment, to accumulate data for secondary analysis. In order to accomplish that, working e-commerce platform was updated, to include all combinations of cognitive biases and their visual executions, described previously. The tracking was set up also, enabling all required variable data to be recorded.

As the platform on which the experiment was conducted possesses weekly seasonality, the experiment was running for a full week, to protect against possible errors that seasonality may cause. What is more, changed pages were rotating evenly with control group, which had no cognitive bias message and visual execution that according to theory would have no effect on consumer behavior modification. This specific page with "control" set of variables was used as a control group to measure performance of other cognitive bias and visual execution combinations. As mentioned before, each message activating different cognitive bias was presented in two colors: red and green. Below (Table 4) you will find translated versions of each message:

Table 4. Messages Triggering Cognitive Biases

Cognitive Bias	Original Message (Lithuanian)	Adapted Message (English)	Reasoning Behind the message
Countdown Effect	Užsisakyk patiekalą per [timer] ir pristatysime iki [delivery time]!	Order your meal in [timer] and we will deliver it to you by [delivery time]!	The timer and projected delivery time creates a sense of urgency, which makes it easier to trigger heuristic thinking (Tversky & Kahneman, 1974)
Bandwagon Effect	Šį patiekalą pristatėme jau 100+ klientų! Užsisakyk ir tu!	This meal was already delivered to 100+ clients! Be one of them - order!	The number of clients shows how many people have already made decision which is already being considered by subject. This creates the sense of crowd action and triggers heuristic thinking of the subject

			(Tversky & Kahneman, 1974).
Loss Aversion	Patiekalas jau rezervuotas! Nepraleisk progos ir užsisakyk!	The meal is already reserved! Do not miss a chance to order it!	By informing about reservation, the sense of already made purchase is stimulated. What is more, supporting text states that by not making decision subject will lose an opportunity to order. This once again triggers the heuristic thinking of the subject (Tversky & Kahneman, 1991)
Gain Effect	Greičiau užsakysi – greičiau gausi!	The faster you order – the faster you get!	Simple gain is presented. Strong statement creates the sense of already acquired gain. Not using it – would mean potential losses. By this setup , heuristic thinking is triggered (Tversky & Kahneman, 1991)

The phrases listed above, were constructed mainly using the formulation and theory presented by Tversky, Kahneman et al. and already used in their previous experiments (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991) (Haselton, Nettle, & Andrews, 2005) (Wilke & Mata, 2012).

To continue with, the colors for visual execution of cognitive biases' were chosen according to guidelines by Lichtlé (2007), Allagui & Lamoine (2008), Biers & Richards (2005) and others. The colors maintained similar levels of hue and saturation, so that they would be equally visible (Lichtlé, 2007). The only difference was in color. The table below presents detailed view on colors used in the experiment:

Color	Color Code
Red	#cd1d36; RGB (205,29,54)
Green	#90c200; RGB (144,194,0)

2.5.1 Experiment Implementation and Data Collection. Constructed experiment model was programmed and launched on working e-commerce food ordering platform "Foodout.lt", with equal rotation setup for each combination of cognitive biases and visual execution of these.

After the experiment was finished and data was collected, the SPSS statistical analysis software was used to test variable relationships and possible means of interaction.

"Foodout.lt" is the biggest online food ordering platform in Lithuania. It is operating in three major cities of this country: Vilnius, Kaunas and Klaipeda. The platform itself does not have even distribution of visitors and sessions over time. Aside from general seasonal (summer, autumn, winter and spring) fluctuations the site has very clear weekly session fluctuations: weekends usually have 30% more sessions than weekday average. The session distribution on Fridays, Saturdays and Sundays is more or less equal throughout the whole day, however the rest of the weekdays have clear peak-times of sessions and orders, which happen twice a day (during lunch from ~11:30 to ~14:00 and dinner from ~17:00 to 20:00). The platform records around 21 000 weekly sessions. The data used for this research was collected for seven days, starting on 2016-03-24 and finishing on 2016-03-01.

In the case of this particular experiment, not all pages of the site were affected by cognitive biases and their visual execution combinations. For the sake of simplicity of measurement and implementation only one of the final pages in customer journey – meal page – was chosen to be equipped of content corresponding independent variables. Meal page can be seen once customer has already navigated to the restaurant and is considering putting something to his purchase basket. Usually, around 15% of all visitors used to navigate to this page, so a sample of ~3000 unique users and sessions could be expected. Desktop visitors accounts for ~70% of whole site traffic. Since the platform was optimized for desktop devices only, big performance discrepancies were being expected.

2.**5.2 Participants and Sampling.** The running e-commerce platform was prepared to perform various A/B tests on meal pages over the course of the week. This timespan was chosen because of previously described patterns of fluctuations. Having the test running for a whole week eliminated possible asymmetry of the data. Following this logic, a total of 9 different order page combinations were plugged in to rotate evenly over time. What is more, during the course of the experiment amount of sessions to the site was equal to around 21 000 sessions. Out of these roughly 18% of visitors navigated to the meal order page, which in this case was equipped with cognitive bias and visual execution combinations (Appendix 1).

A weekly test on this platform guaranteed at least 400 unique session views for each of the page combinations, which would generate sufficient amount of data to perform secondary analysis, since each of previously mentioned dependent variables were also being tracked for each session and page view.

It is important to mention, that e-commerce platform on which experiment was performed, possessed weekly seasonality. To cancel possible errors that may emerge from daily session fluctuations, test was run for a weekly period; all visitors of site were chosen to participate in the experiment. What is more, page combinations (cognitive biases and visual execution) were tied to each session, so that each visitor would see only one combination during his or hers visit (so that no uncertainty and frustration would be generated).

All participants were living in one of three biggest Lithuanian cities (Vilnius, Kaunas or Klaipeda). Male and female distribution was even at roughly 50 percent. The total (weekly) sample consisted of 21 000 unique sessions. Each of the pre-defined page setups got similar number of views, since they were programmed to rotate evenly.

2.6 Ethical Considerations

All participants of the experiment were participating without any notification, in order to not influence their behavior by any means. No legal or ethical rules and/or laws were affected or violated by conducting the experiment.

2.7 Weaknesses and Limitations of the Research Design

Possibly, there are several limitations of the applied research model. To begin with, the experiment itself took only a week. It may be not enough to capture the full fluctuations and changes in customer behavior.

To add up, having an experiment only with several pages within a platform may have created unwanted confusion and discomfort for consumers, thus influencing their natural behavior and information perception.

2.8 Internal and External Validity

In terms of this research, internal validity shows how accurate the experiment was and how accurately the changes of the dependent variables are explained by independent variables

(McDermott, 2011). External validity, on the other hand, evaluates how the results of this experiment could be applicable to the real life settings (McDermott, 2011). It is crucial to evaluate possible limitations in these dimensions.

In terms of this research, internal validity was ensured by adopting means of data analysis that are widely tested and accepted by scholars and e-commerce professionals. The A/B test was performed, totaling of 9 different order page setups, which resulted from manipulation with two independent variables (cognitive biases and their visual execution, together with control page without any biases and with neutral color). What is more, possible errors caused by seasonality fluctuations were eliminated – the experiment was running for a whole fluctuation period. On the other hand, the subjects may have had different set of preferences, values or even level of hungriness. What is more, some may have been affected by possible actions of competitors. No precautions were taken against these factors; however the same levels of errors may have been expected throughout all groups of participating subjects.

External validity was secured by high level of randomization of participants. What is more, precautions against unnatural behavior were taken (the participants were not informed about experiment in progress) and no additional activities were happening, in order to keep natural flow and distribution of consumers. The experiment was conducted in real life setting, thus it provided high level of external validity.

3. Empirical Research Results

In this part of the paper, the results of quantitative data analysis are presented. As mentioned before, the data was collected by conducting an experiment on running e-commerce platform.

Analysis of variance (ANOVA) testing was chosen as the main tool of examination, since we will be looking at variations of different groups of customers, which were provided with mixed variations of visual properties stimulating cognitive biases.

3.1 Descriptive Statistics

The experiment ran for 7 days, including weekdays and weekend. The different page combinations were set to rotate randomly. The randomization sequence was tied to unique session of the webpage. In this way it was ensured, that one person will see only one cognitive bias and visual execution combination per unique site visit. In the table below, the session distribution of pages included in experiment is presented.

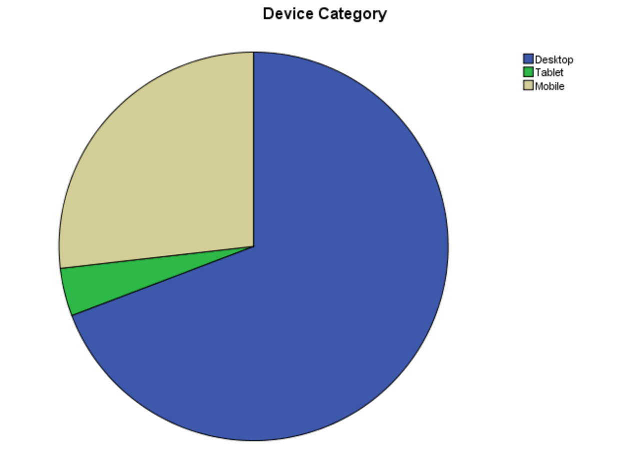
Table 5. Session distribution

Color	Cognitive Bias	Sessions	Percentage
Red	Countdown Effect	443	11.61%
	Bandwagon Effect	419	10.98%
	Loss Aversion	434	11.37%
	Gain Effect	408	10.69%
Green	Countdown Effect	434	11.37%
	Bandwagon Effect	421	11.03%
	Loss Aversion	422	11.06%
	Gain Effect	455	11.92%
Control	Control	380	9.96%

As it can be seen from Table 2, the sessions' distribution was somewhat similar to all cognitive biases' and visual execution combinations. What is more, the experiment was performed on a website, which is not mobile-friendly. However, it still can be accessed from multiple devices. The recorded sessions' distribution among different devices is presented in the Table 3.

Table 6. Device Distribution

Device	Sessions	Percentage
Desktop	2641	69.21%
Tablet	152	3.98%
Mobile	1023	26.81%



The dominance of desktop devices can be easily seen. Tablets and mobile devices accounts for approximately 30% of the whole sessions. Importantly, this part of the recorded interactions with e-commerce platform will be taken into consideration, as the website is optimized for desktop only, and sessions from other types of devices may distort the results of the experiment.

3.2 Testing the Significance of Device

Taking into account the technical limitations of e-commerce platform on which the experiment was performed, the implication could be drawn, that the same setup of cognitive bias and its visual execution will perform differently on desktop and other devices. To test that empirically, independent samples t-test was performed on the collected data. Two comparisons were made:

- Desktop versus Mobile devices;
- Desktop versus Tablet devices.

The t-test with first case provided following results:

Table 7. Desktop versus Mobile devices

	Device Category	N	Mean	Std. Deviation	Std. Error Mean	F	Significance (2-tailed)
Page Value	Desktop	2641	7.444551	14.5158204	.2824603	94.399	.000
	Mobile	1023	3.785809	8.1269284	.2540906		
Pageviews	Desktop	2641	4.12	5.673	.110	97.403	.000
	Mobile	1023	2.51	2.414	.075		
Time on Page	Desktop	2641	107.41	269.417	5.243	40.001	.000
	Mobile	1023	62.89	167.092	5.224		
Conversion	Desktop	2641	.3658	.48174	.00937	457.582	.000
	Mobile	1023	.2111	.40832	.01277		

As it can be seen from this model, significance levels of p-value are less than 0.05 for each dependent variable. What is more, the mobile devices have significantly lower mean scores compared to desktop ones. In terms of this research, the experiment was designed having desktop devices in mind and these results proves, that people who accessed the pages with experiment materials plugged in, behaved differently from others. To add up, mobile devices scored significantly worse on each variable, compared to desktop counterparts. Thus mobile devices' score will be excluded in further analysis, so that they would not distort the data distribution.

To continue with, the t-test in the same manner was performed to measure scores for desktop versus tablet devices (Table 5).

Table 8. Desktop versus Tablet devices

	Device Category	N	Mean	Std. Deviation	Std. Error Mean	F	Significance (2-tailed)
Page Value	Desktop	2641	7.444551	14.5158204	.2824603	.658	.725
	Tablet	152	7.146513	9.8494723	.7988977		
Pageviews	Desktop	2641	4.12	5.673	.110	10.098	.000
	Tablet	152	3.10	2.513	.204		
Time on Page	Desktop	2641	107.41	269.417	5.243	7.699	.002
	Tablet	152	72.49	123.452	10.013		
Conversion	Desktop	2641	.3658	.48174	.00937	1.059	.583
	Tablet	152	.3882	.48894	.03966		

In the case where desktop devices were compared to their tablet counterparts, some differences from precious comparison of desktop versus mobile can be seen. First of all, the difference in sessions should be mentioned: mobile devices can be accounted for ~26% of whole experiment sessions, whereas tabled counterparts correspond only ~4%. To continue with, in t-test comparison of desktop versus tablets, the p-value of less than 0.05 can be observed with two out of four dependent variables (page views and time on page). Other two variables (page value and conversion) scored significantly higher in terms of p-value, thus it could be concluded, that with tablet devices only page views and time on page values are significantly different from desktop device scores. However, because of low amount of observations and somewhat different results among dependent variables tablet device scores will be excluded in following calculations, as well as mobile counterparts in order to increase overall desktop devices' data accuracy even more. The following calculations will be performed on data collected from desktop devices only.

3.3 Testing the Effects of Cognitive Biases and Their Visual Execution

Once the data sample was cleaned out from bad performing groups of devices (mobile and tablet), it was possible to dive-in to more detailed analysis on cognitive biases and their visual execution effects on Foodout.lt consumer behavior.

To begin with, one-way ANOVA test was ran on the selected dataset, cognitive biases were plugged in as an independent variable (Table 6):

Table 9. ANOVA on Cognitive Biases & Dependent Variables

		N	Mean	Std. Deviation	Std. Error Mean	F	Significance
Pageviews	Control	251	1.10	.624	.039	20.684	.000
	Countdown	610	4.38	5.230	.212		
	Bandwagon	601	4.51	6.870	.280		
	Loss Aversion	600	4.64	6.248	.255		
	Gain Effect	579	4.23	4.908	.204		
Page Value	Control	251	6.474861	11.3061125	.7136355	1.196	.311
	Countdown	610	6.799419	15.5447009	.6293865		
	Bandwagon	601	8.079407	17.4867016	.7132974		
	Loss Aversion	600	8.085409	13.0401880	.5323634		
	Gain Effect	579	7.221509	12.5351690	.5209438		
Time on Page	Control	251	44.91	114.378	7.219	4.160	.002
	Countdown	610	123.05	308.580	12.494		
	Bandwagon	601	110.54	250.778	10.229		
	Loss Aversion	600	117.51	314.196	12.827		

	Gain Effect	579	104.31	236.380	9.824		
Conversion	Control	251	.3267	.46994	.02966	2.314	.055
	Countdown	610	.3279	.46982	.01902		
	Bandwagon	601	.3744	.48436	.01976		
	Loss Aversion	600	.4017	.49064	.02003		
	Gain Effect	579	.3765	.48493	.02015		

Out of the statistical data analysis results above, the null hypothesis stating that cognitive biases have no effect on each of dependent variables, can be instantly rejected in terms of page views and time on page. In both cases, p-values of each variable are less than minimum tolerance level of 0.05, thus it can be stated, that the rejection of second research hypothesis (H2) was failed – cognitive biases do have significant effects on consumer engagement in e-commerce platforms in terms of page views per session and time spent on pages. In some cases, many viewed pages and long period of time spent on single page may signal bad information provision and complicated site hierarchy. However, in this particular case, the content and site page structure was not affected, so the increase in time spent on page together with the number of viewed pages actually signals better engagement with the content of the e-commerce platform.

Alternatively, cognitive biases' p-value on page value is much higher than maximum tolerance level of 0.05. The null hypothesis stating that cognitive biases have no effect on revenue generation cannot be rejected. In other words, third research hypothesis (H3) can be rejected also – cognitive biases do not have effect on revenue generation.

In order to better explore and understand how each bias affect dependent variables and how the scores differs from control group, a series of post-hoc tests were performed (Table 10):

Table 10. Post-Hoc Tests on Cognitive Biases

Dependent Variable	(I) Cognitive Bias	(J) Cognitive Bias	Mean Difference (I-J)	Std. Error	Sig.
Pageviews	Control	Countdown	-3.278*	.419	.000
		Bandwagon	-3.404*	.420	.000
		Loss Aversion	-3.538*	.420	.000
		Gain Effect	-3.123*	.422	.000
	Countdown	Control	3.278*	.419	.000
		Bandwagon	-.126	.321	1.000
		Loss Aversion	-.260	.321	1.000
		Gain Effect	.156	.324	1.000
	Bandwagon	Control	3.404*	.420	.000
		Countdown	.126	.321	1.000
		Loss Aversion	-.134	.323	1.000
		Gain Effect	.281	.326	1.000
	Loss Aversion	Control	3.538*	.420	.000
		Countdown	.260	.321	1.000
		Bandwagon	.134	.323	1.000
		Gain Effect	.415	.326	1.000
	Gain Effect	Control	3.123*	.422	.000
		Countdown	-.156	.324	1.000
		Bandwagon	-.281	.326	1.000
		Loss Aversion	-.415	.326	1.000
Page Value	Control	Countdown	-.3245587	1.0883712	1.000
		Bandwagon	-1.6045464	1.0907443	1.000
		Loss Aversion	-1.6105489	1.0910121	1.000
		Gain Effect	-.7466484	1.0968321	1.000
	Countdown	Control	.3245587	1.0883712	1.000
		Bandwagon	-1.2799877	.8341558	1.000
		Loss Aversion	-1.2859902	.8345059	1.000
		Gain Effect	-.4220897	.8421006	1.000
	Bandwagon	Control	1.6045464	1.0907443	1.000
		Countdown	1.2799877	.8341558	1.000
		Loss Aversion	-.0060025	.8375985	1.000

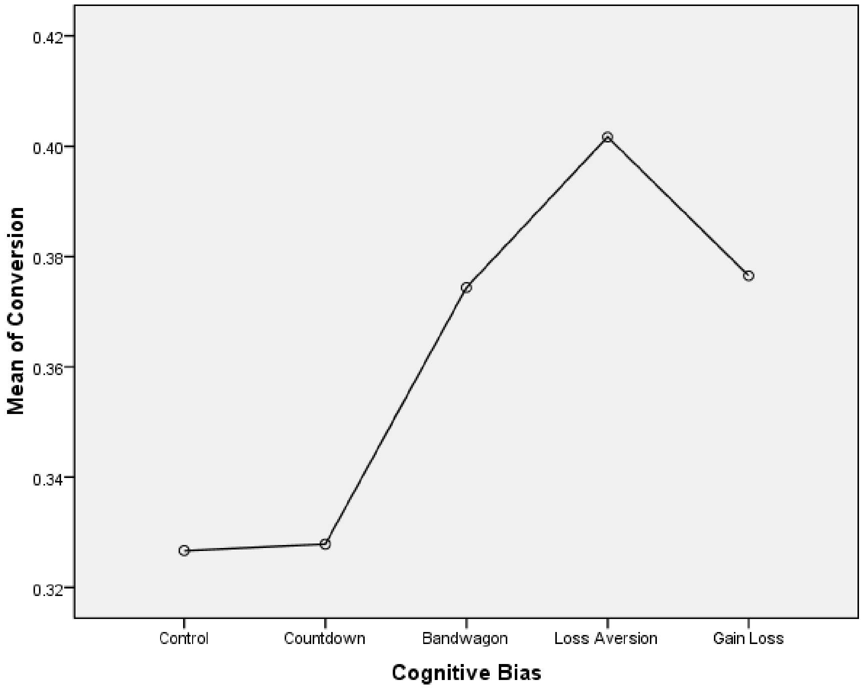
		Gain Effect	.8578980	.8451655	1.000
	Loss Aversion	Control	1.6105489	1.0910121	1.000
		Countdown	1.2859902	.8345059	1.000
		Bandwagon	.0060025	.8375985	1.000
		Gain Effect	.8639005	.8455110	1.000
	Gain Effect	Control	.7466484	1.0968321	1.000
		Countdown	.4220897	.8421006	1.000
		Bandwagon	-.8578980	.8451655	1.000
		Loss Aversion	-.8639005	.8455110	1.000
Time on Page	Control	Countdown	-78.135*	20.155	.001
		Bandwagon	-65.628*	20.199	.012
		Loss Aversion	-72.594*	20.204	.003
		Gain Effect	-59.400*	20.312	.035
	Countdown	Control	78.135*	20.155	.001
		Bandwagon	12.507	15.447	1.000
		Loss Aversion	5.541	15.454	1.000
		Gain Effect	18.735	15.595	1.000
	Bandwagon	Control	65.628*	20.199	.012
		Countdown	-12.507	15.447	1.000
		Loss Aversion	-6.966	15.511	1.000
		Gain Effect	6.228	15.651	1.000
	Loss Aversion	Control	72.594*	20.204	.003
		Countdown	-5.541	15.454	1.000
		Bandwagon	6.966	15.511	1.000
		Gain Effect	13.194	15.658	1.000
	Gain Effect	Control	59.400*	20.312	.035
		Countdown	-18.735	15.595	1.000
		Bandwagon	-6.228	15.651	1.000
		Loss Aversion	-13.194	15.658	1.000
Conversion	Control	Countdown	-.00118	.03609	1.000
		Bandwagon	-.04768	.03617	1.000
		Loss Aversion	-.07497	.03618	.383
		Gain Effect	-.04982	.03637	1.000
	Countdown	Control	.00118	.03609	1.000
		Bandwagon	-.04651	.02766	.928

		Loss Aversion	-.07380	.02767	.077
		Gain Effect	-.04864	.02792	.816
	Bandwagon	Control	.04768	.03617	1.000
		Countdown	.04651	.02766	.928
		Loss Aversion	-.02729	.02777	1.000
		Gain Effect	-.00214	.02802	1.000
	Loss Aversion	Control	.07497	.03618	.383
		Countdown	.07380	.02767	.077
		Bandwagon	.02729	.02777	1.000
		Gain Effect	.02516	.02804	1.000
	Gain Effect	Control	.04982	.03637	1.000
		Countdown	.04864	.02792	.816
		Bandwagon	.00214	.02802	1.000
		Loss Aversion	-.02516	.02804	1.000

The post-hoc tests prove the previous findings: cognitive biases show significant differences from control groups for page views and time on page, whereas there are no differences in terms of page value. For these particular variables there are no significant differences among cognitive biases itself. However, some more fluctuations can be observed within the groups when examining conversion variable. It can be seen, that there are some differences not among control group and cognitive biases only, but also within different biases too. The relationships between different cognitive biases and their influence on conversion of the e-commerce platform are examined in the following chapter.

3.3.1. Cognitive Biases & Conversion Relationship. Finally, the most interesting outcome of ANOVA test could be observed with cognitive biases effect analysis on conversion rate of e-commerce platform. The p-value is equal to 0.055, which is just a bit higher than maximum tolerance level. As the difference is relatively small, let us take a look at the mean values for each cognitive bias:

Figure 3. Cognitive Bias Means of Conversion



The graph above visualizes the mean values of conversion for each cognitive bias (Table 6). It can be clearly seen, that countdown effect scores are similar to those of control group. However remaining cognitive biases records much higher mean values. Since p-value of conversion (Table 6) is very close to maximum tolerance level, these three cognitive biases with highest mean scores (Bandwagon effect, Loss Aversion, Gain and Loss effect) were chosen to perform more detail examination. T-test mean analysis was chosen to be conducted, since with it significance levels could be checked for each cognitive bias. The analysis generated following results:

Table 11. T-test on Each Cognitive Bias

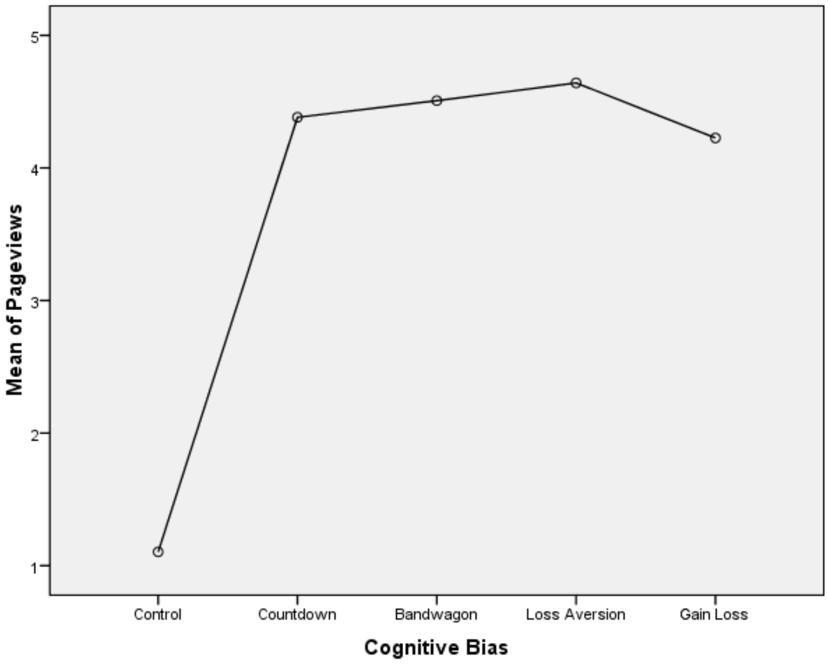
		N	Mean	Std. Deviation	Std. Error Mean	F	Significance
Conversion	Control	251	.3267	.46994	.02966		
	Bandwagon	601	.3744	.48436	.01976	7.881	.187
	Loss Aversion	600	.4017	.49064	.02003	20.414	.040
	Gain Effect	579	.3765	.48493	.02015	8.495	.170

With this test, three cognitive biases (Bandwagon Effect, Loss Aversion and Gain Effect) were compared against control group in terms of conversions, as countdown effect was already rejected from the further testing for being too similar to control group.

It can be seen in the table above, t-test returned p-values, which were much higher than maximum confidence level of 0.05 for two of three tested cognitive biases: bandwagon effect and Gain Effect effect. Interestingly, loss aversion bias scored p-value equal to 0.04, which is below maximum level of confidence, so in this particular case null hypothesis can be rejected, thus meaning that some specific cognitive biases might have an effect on conversions in e-commerce platforms. With this t-test result on loss aversion cognitive bias in mind, the first research hypothesis (H1) cannot be rejected, even though the initial p-value of ANOVA test on conversion variable was above confidence level. In fact, despite the lack of strong evidence we still can state that cognitive biases have positive effect on conversions in e-commerce platforms.

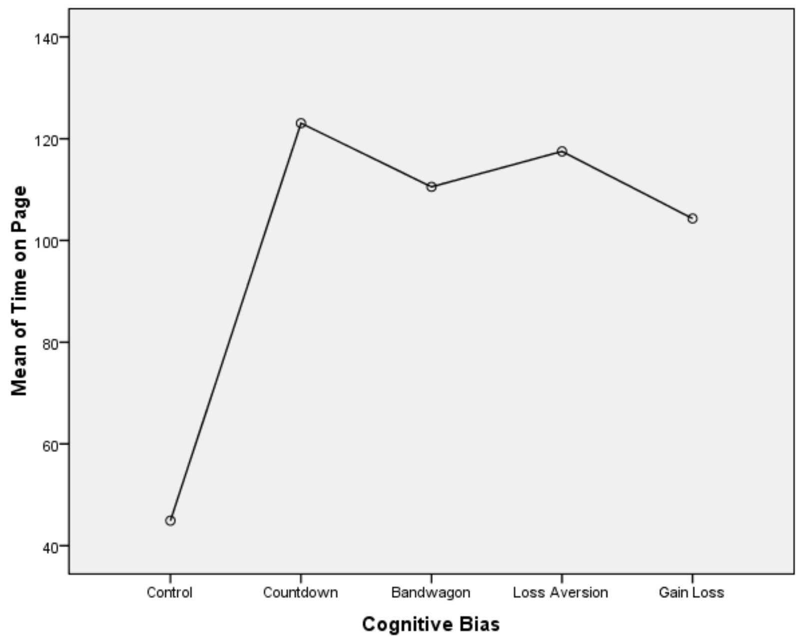
3.3.2. Countdown Effect – Dominating Cognitive Bias? To continue with, fourth research hypothesis (H4) stated, that countdown effect will have the biggest effect on dependent variables, assuming already widely used practice by some e-commerce platforms, to employ this particular tool in order to affect consumer behavior. It was decided to evaluate mean scores of countdown cognitive biases (Table 6), for the respective dependent variables where cognitive biases showed significant differences. It can be clearly seen, that this particular tool is not performing the best with each dependent variable:

Figure 4. Cognitive Bias Means of Pageviews



In terms of performance on page views per session, countdown effect is performing very similarly to the other biases.

Figure 5. Cognitive Biases Means of Time on Page



However, countdown effect effectively increases the time customers of e-commerce platforms spend on page. This may signal higher engagement with the content.

As already mentioned before it can be clearly seen (Figure 2), that in this particular experiment countdown effect did not had almost any result on conversion increase. No comparison for page value is provided, as the significance of cognitive biases was above the maximum tolerance level, thus biases had no effect on this dependent variable in the first place.

To continue with, previously performed post-hoc tests (Table 10) did not indicated any significant differences between countdown bias and any other cognitive bias. Thus it can be stated, that countdown bias does not have dominating performance compared to other cognitive biases.

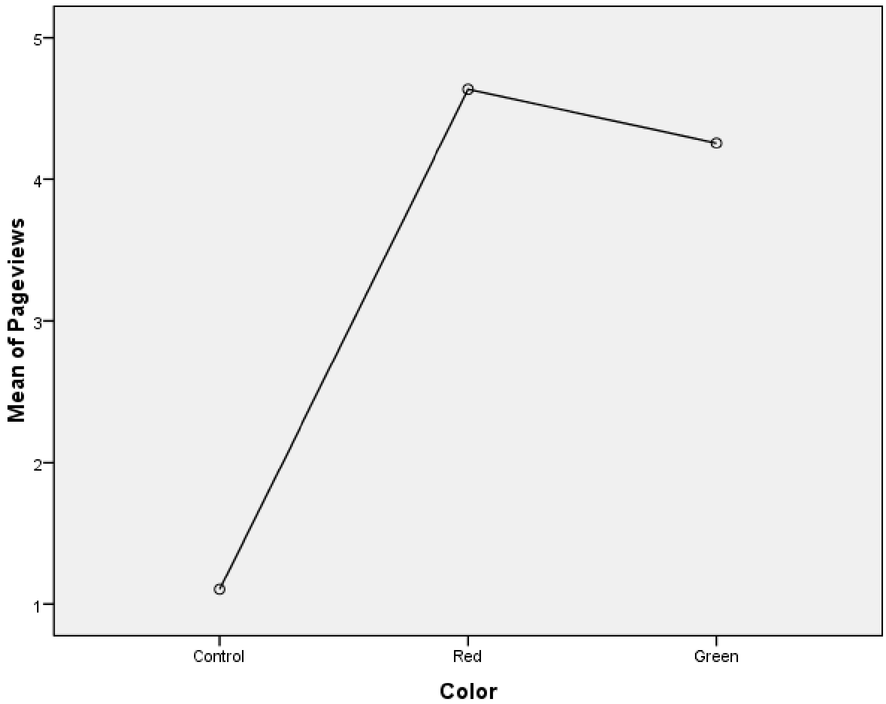
3.3.3. Employing Visual Execution. The one way ANOVA test results on visual execution are provided below:

Table 12. ANOVA on Visual Execution and Dependent Variables

		N	Mean	Std. Deviation	Std. Error Mean	F	Significance
Pageviews	Control	251	1.10	.624	.039	41.898	.000
	Red	1167	4.63	6.258	.183		
	Green	1223	4.26	5.472	.156		
Page Value	Control	251	6.474861	11.3061125	.7136355	1.915	.147
	Red	1167	8.035608	14.9085776	.4364161		
	Green	1223	7.079570	14.7079149	.4205696		
Time on Page	Control	251	44.91	114.378	7.219	7.500	.001
	Red	1167	114.14	274.117	8.024		
	Green	1223	113.81	285.575	8.166		
Conversion	Control	251	.3267	.46994	.02966	2.719	.066
	Red	1167	.3890	.48774	.01428		
	Green	1223	.3516	.47766	.01366		

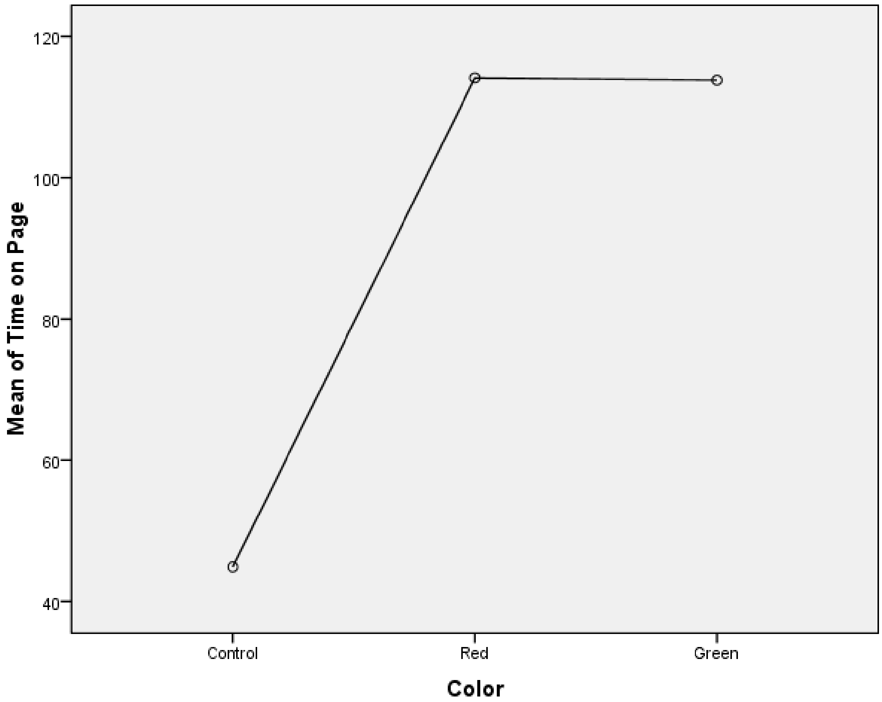
It is important to mention, that in the conducted experiment, only cognitive biases were equipped with different visual execution properties. So the significance levels of visual execution are highly related with those of cognitive biases. Alternatively, in this case the main point of importance of visual execution is the color mean effect on dependent variables, not the significance value (which is naturally mirroring those of cognitive biases in some sort). In order to assess this parameter, the mean values of the colors should be examined:

Figure 6. Color Means of Pageviews



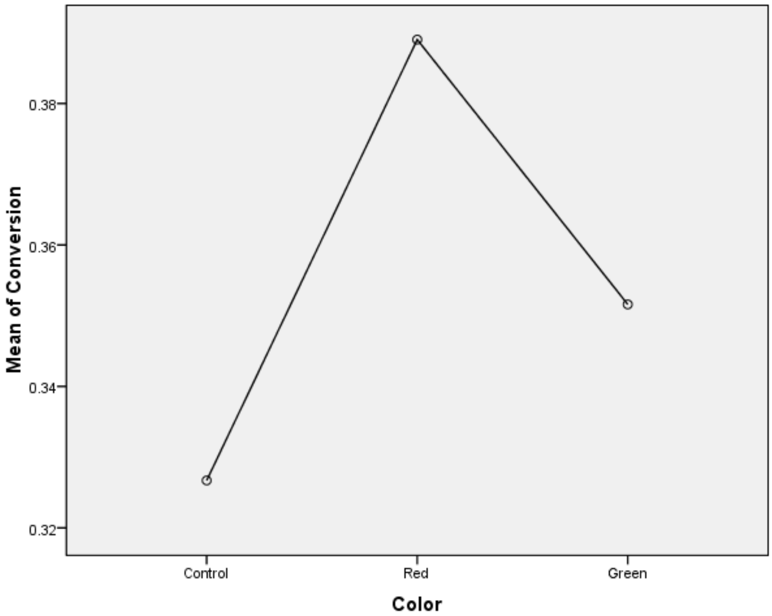
In the picture above, we can see that both experiment colors (Red and Green) had much better results compared to control group of site sessions. However, the slight lead in performance is held by red color (Table 8).

Figure 7. Color Means of Time on Page



Alternatively, in terms of time on page, no difference in red or green color can be observed (Figure 6). However, the difference in color adoption in general can be observed.

Figure 8. Color Means of Conversion



Finally, a clear lead by red color can be observed in terms of conversions (Figure 7). Once again, in the initial color ANOVA model significance levels were above the maximum tolerance level of 0.05, however the cognitive biases in this experiment were equipped with one of two colors (red or green), so in this case the color effect in terms of average mean was the main focus.

Having these results in mind the fifth hypothesis of the research (H5) cannot be dismissed just yet – red color does show the highest positive effects on dependent variables.

To better explore the effects of color and cognitive biases interaction, two-way ANOVA tests were performed, to better picture the interaction effects. Two dependent variables were chosen: page views and time on page, as they were scoring significant p-values for both cognitive biases and visual execution.

For the first dependent variable (page views) the following results were calculated:

Table 13. Two-Way ANOVA on Pageviews

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3053.818[a]	8	381.727	12.266	.000	.036
Intercept	30103.039	1	30103.039	967.288	.000	.269
CognitiveBias	37.891	3	12.630	.406	.749	.000
Color	88.956	1	88.956	2.858	.091	.001
CognitiveBias * Color	387.418	3	129.139	4.150	.006	.005
Error	81910.694	2632	31.121			
Total	129877.000	2641				
Corrected Total	84964.512	2640				

And for the second dependent variable (time on page) returned results were these:

Table 14. Two-Way Anova on Time on Page

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1.756E6	8	219545.467	3.043	.002	.009
Intercept	2.133E7	1	2.133E7	295.702	.000	.101
CognitiveBias	94629.132	3	31543.044	.437	.726	.000
Color	232.987	1	232.987	.003	.955	.000
CognitiveBias * Color	554192.092	3	184730.697	2.561	.053	.003
Error	1.899E8	2632	72138.596			
Total	2.221E8	2641				
Corrected Total	1.916E8	2640				

It can be seen, that significance level (p-value) for cognitive biases and color interaction in terms of page views is much smaller than minimum required value of 0.05. On the other hand, the significance level for same interaction in terms of Time on Page is just a little higher (p=0.053) than minimum required value. Based on these, the null hypothesis still can be rejected, because the interaction effect is significant at least for page views. Alternatively, the hypothesis H5 cannot be rejected confidentially, thus it can be stated that red color indeed can increase the effectiveness of cognitive biases.

3.4 Answering Research Question. Summary of Hypotheses' Tests

In order to answer initial research question, the findings the results on previously stated hypotheses (Table 2) should by systemized. In order to do that, the following table was constructed, to better visualize results of data analysis performed in previous chapters of the paper.

Table 15. Hypotheses and Outcomes

Hypothesis	Description	Outcome
H1: Cognitive Bias will have a positive effect on conversion rate.	Presence of cognitive bias will increase the number of conversions within the tested group.	Failed to reject
H2: Cognitive Bias will have a positive effect on customer engagement.	Presence of cognitive bias will increase viewed pages' number together with page view time.	Failed to reject
H3: Cognitive Bias will have a positive effect on revenue generation.	Presence of cognitive bias will increase revenue generated during session on website (will generate higher page value).	Rejected
H4: Countdown effect will have the biggest effect on dependent variables	Since countdown variations are already widely used in e-commerce platforms, assumption is made, that it should give the biggest positive effects on sites.	Rejected
H5: Cognitive biases with red color visual execution will have the biggest positive effect	According to its stimulating properties, red color should increase the positive effects of	Failed to reject

on dependent variables in comparison to the same biases with green color visual execution.	cognitive biases on dependent variables	

H1: in order to test this hypothesis, ANOVA test was run. Dependent variable “conversions” was equipped with True/False values, whether a conversion was recorded during the session. After the calculations were made, the p-value of 0.055 was returned (Table 9). However, it was decided to perform several more tests, potentially possessing higher accuracy, as there were some significant differences in means of each cognitive bias that was put on experiment. More accurate t-test was performed to examine what impact does each cognitive bias has on conversions, and Loss Aversion cognitive bias scored p-value of 0.04, which was already less than maximum tolerance level of 0.05 (Table 12). Thus, the conclusion could be made, that Loss Aversion has an effect on conversions in e-commerce platform. Consequentially, the hypothesis H1 could not be rejected, even though the first test did not returned p-value less than maximum tolerance level.

H2: In the experiment two dependent variables measured consumer engagement: “Pageviews” and “Time on Page”. Each was presented in nominal scale. The more page views were recorded during given session, the more engaged the subject was with the e-commerce platform. Alternatively, the more time customer spent on page, the more engaged he or she was with the content provided on that particular page.

During tests against this particular hypothesis, cognitive biases instantly scored significant p-values (Table 9). Thus the null hypothesis could be rejected and the final conclusion on cognitive biases effect in engagement with e-commerce platforms could be made – cognitive biases do have significant effect on consumer engagement with website, so the hypothesis H2 could not be rejected.

H3: the dependent variable corresponding revenue generation of the site was “Page Value”. It was measured in nominal scale. The logic behind this variable is very simple – each time the purchase was made, the platform assigned the conversion value to the particular page session. In other words, the more value was generated, the higher page value was supposed to be. Also, the presence of any value in this field, signaled, that conversion was made in general.

ANOVA test for this variable produced relatively high p-value (Table 9), which was significantly higher than maximum tolerance level of 0.05. Because of such result, null hypothesis was failed to reject, consequentially, the hypothesis H3 was rejected – the employment of cognitive biases did not show any effect on general revenue that e-commerce platform generated per session.

H4: the assumption was made, that since the countdown effect possesses and activates several cognitive biases at once, also it is already widely used by many e-commerce platforms it should record significantly better results than other cognitive biases that were plugged into experiment. In order to achieve that, the mean values of each cognitive bias were compared for each of dependent variable (Table 9). Interestingly enough, countdown effect did not dominated other cognitive biases, thus the null hypothesis was failed to reject. Alternatively, the hypothesis H4 was rejected – countdown effect did not have the biggest impact on each of dependent variables.

H5: the following hypothesis stated that visual execution (in this particular case – red color) will have the biggest significant effect on cognitive bias activation: all messages in the experiment were colored in two colors: red and green. According to the theory presented in Literature Review part, red color possessed the set of stimulating properties, which would make cognitive bias message more visible, thus better understandable. Consequentially, if the message is seen and read by the subject, the chances of triggering person's heuristic thinking increase significantly.

ANOVA testing (Table 12) provided very similar results to the ones that cognitive biases scored (Table 9) in terms of significance values. However, it is perfectly normal, since each message was equipped with the color. The most important part in this case was to examine the effect different colors have on each dependent variable. After revising these values (Table 11) and performing additional two-way ANOVA tests (Table 13 and Table 14) the null hypothesis could be rejected. In other words hypothesis H5 was failed to reject – red color does have the most significant positive effect on dependent variables.

Having an overview on the research hypotheses the research question can be answered, which was following: how cognitive biases and their visual execution affect consumer behavior in e-commerce platforms? Consequently, relying on the empirical results, it can be stated, that cognitive biases and specific visual execution (which could increase levels of alertness, awareness and boost visibility and information perception in general) of their, affect consumer behavior in following ways:

- Increases engagement: both on-site and on-page;
- Increases conversion rate of the e-commerce platform.

What is more, it can be concluded, that visual execution is important part of employing cognitive biases, because these combinations with stimulating and engaging color (red) performed better than counterparts with calming, yet still visible color (green).

4. Discussion

4.1. Main Findings

The empirical research, which was carried out, contributes to better understanding of the effects cognitive biases and their visual execution has on consumer behavior online – e-commerce platforms in particular. The major work in the field of cognitive biases was done by Daniel Kahneman and Amos Tversky. The concept itself brought a lot of controversy: on one hand, it started a new movement of behavioral psychology, which afterwards naturally moved to business and marketing researches. The idea of addressing human thinking in a deeper level, thus enabling to push individuals towards specific, predefined decisions was appealing to many (Oechssler, Roider, & Schmitz, 2009) (Reddi & Carpenter, 2000) (Wilke & Mata, 2012). On the other hand, there were many not so thrilled scholars, which criticized the concept of cognitive biases (Gigerenzer, 1991) (Gigerenzer & David, 1987) (Gigerenzer & Todd, 1999). One of the most active critics, Gerd Gigerenzer wrote: "practicing statisticians start by investigating the content of a problem, work out a set of assumptions, and, finally, build a statistical model based on these assumptions. The heuristics-and-biases program starts at the opposite end" (Gigerenzer, 1996), thus pointing out, that the existence of such thinking patterns discussed by Tversky, Kahneman and others may be questioned, since the initial works on the theory followed different flow of research.

In this paper, both sides were critically evaluated, providing general ideas behind cognitive biases as a concept and possible limitations of this theory. To continue with, as the main point of interest was effects cognitive biases has on consumer behavior in e-commerce platforms, the main proxy of communicating the biases had to be chosen. After reviewing possible means of visual execution, color as the most effective feature was chosen.

In order to empirically test previously mentioned theoretical concepts, experiment was carried out: different combinations of cognitive biases and their visual setups were put on working e-commerce platform. Once the data was collected, the methods of quantitative data analysis were applied, to examine the interactions.

To begin with, data was collected after a week of equal rotation of cognitive biases and their visual execution combinations on e-commerce platform. There were no limitations on the experiment itself, so people with different levels of consideration may have participated. More importantly, the site itself was not compatible with mobile devices. However, around 30% of all collected data was from smartphones and tablets. Several tests were run in order to examine the experiment performance among device groups. As it could already been expected, mobile devices scores on consumer behavior variables were significantly different to their desktop counterparts. What is more, the scores were significantly worse, so it was proved, that in this particular case, e-commerce site did not perform well with smartphones and tablets. Therefore decision was made to eliminate mobile from the further research and analysis.

Further step was to analyze the distribution of cognitive biases and their visual execution distribution. The total number of possible combinations was equal to 9 (four cognitive biases: countdown effect, bandwagon effect, loss aversion, gain versus loss; two setups of visual execution: green and red; and one control group: no cognitive bias assessment and neutral color – brown) (Appendix 1). Each combination was randomly assigned to each website session (so theoretically the distribution may have been distorted). However, the distribution appeared to be normal and no measures were taken. It was possible to proceed to the next steps of analysis.

Once bad performing groups distorting the results were removed and distribution was checked, a round of ANOVA tests were run, in order to evaluate the significance chosen cognitive biases have on consumer behavior. During the first set of testing two engagement variables (page views and time on page) showed significant results. This meant that cognitive biases have a positive effect on customer engagement with the platform. During conducted experiment, individuals tend to stay on specific site pages longer and interact with more of them, which meant higher possibilities of getting more information, which naturally increased the probability of possible conversion. This behavior shows that the general concept of cognitive biases described by Tversky & Kahneman (1974) could be transferred and can work through proxies, such as e-commerce platform. However, the page value showed no difference for cognitive biases, thus meaning that equipment of cognitive bias in e-commerce platform will not make experiment subjects to increase the value of their potential purchases. There are several possible explanations to this result: the formulation of bias was not clear enough and did not managed to trigger the pre-decided behavior; the experiment and tracking should be fine-tuned and run for a longer period of time to collect more data; and finally – the setup itself was not efficient enough (Gigerenzer & David, 1987), since the model constructed by Tversky & Kahneman (1974) was followed and the methods behind it received some criticism (Gigerenzer & David, 1987) (Gigerenzer, 1993). What is more, the cognitive biases' triggering messages on the web site were more focused on pushing towards making conversion and not increasing its value. Interestingly, the conversion variable felt shortly above minimum tolerance level, but since it was so close to significance, it was decided to check what impact on conversions had each of cognitive biases. Surprisingly, one of the four cognitive biases (loss aversion) returned significant results after the tests were run. Because of this, the null hypothesis for conversions could not be rejected, thus it was concluded, that cognitive biases do have some signs of having effect on conversion quantity in e-commerce platform. Therefore, the theory behind the works of pro-cognitive biases scholars (Tversky, Kahneman et al.) proved to be working.

Finally, the tests were run on visual execution of cognitive biases, to check whether the properties of colors that stimulate awareness and alertness could improve the perception of cognitive biases, thus increasing the efficiency of overall performance. According to Lichtlé (2007), Aslam (2006) aggressive color such as red should stimulate the visibility and perception of messages equipped with cognitive biases, thus improving the performance of each cognitive bias. In order to empirically evaluate the effects of visual execution of cognitive biases, a set of ANOVA testing was conducted. Since visual combinations were applied together with cognitive biases, so significance levels for each dependent variable were very similar to those previously scored by examining cognitive biases' effects. However, in this case the main point of interest was whether the red color will have the most weight to each of the dependent variable. By comparing the means of colors for each dependent variable it was concluded, that color has a positive effect on information perception, since red had the best performance. What is more, additional two-way ANOVA tests were run, to evaluate the interaction effects of cognitive biases and their visual execution. These brought significant results, so it means that by selecting properties of the color, which stimulates alertness, awareness according to Lichtlé, Aslam et al. and helps to "intensify" the subject, will help him or her to perceive the information better, thus enabling heuristic thinking to trigger effects of cognitive biases better.

In conclusion, the results of the empirical research of this study shows, that cognitive biases and their visual execution has effect on several features of consumer behavior (engagement, willingness to convert) in e-commerce platforms.

4.2 Practical Implications

The findings presented in this research could be used in several ways. First of all, they could be used to draw some more attention to studies examining consumer behavior online. The empirical testing shows, that it is possible to adapt general cognitive biases' behavioral models that were developed by Tversky, Kahneman et al., for usage online. What is more, the main practical implication could be drawn from the results of this research, is that by employing the concepts of cognitive biases and targeting heuristic thinking of human beings it is possible to model their decision flow, thus "pushing" them towards already pre-defined goal or decision, just like in real-time experiments performed by Tversky & Kahneman (1974). To continue with, this paper and the conducted experiment proves, that it is possible to apply these behavioral models not only in direct communication as it was done previously (Simon, 1955) (Tversky & Kahneman, 1974) (Tversky & Kahneman, 1991) (Wilke & Mata, 2012), but also online. To add up, some specific means of communication that differ direct cognitive bias assessment from addressing them online are pointed out and tested: if we take cognitive bias activation in direct communication, the message, triggering the heuristic thinking is the main tool (Tversky & Kahneman, 1974) (Wilke & Mata, 2012). However, if we want to test and exploit the concept online, more dimensions of communication has to be considered (Allagui & Lamoine, 2008) (Alexander, 2006) (Pellet & Papadopoulou, 2009). The possible ways of communication online were discussed and colors were chosen as the most important and the biggest impact generators for receiving the cognitive biases triggering communication messages (Aslam, 2006) (Lichtlé, 2007) (Allagui & Lamoine, 2008). Three different setups of colors were tested: neutral brown, bright calming green and bright alarming red (Aslam, 2006) (Biers & Richards, 2005) (Lichtlé, 2007). After examination of collected data it can be concluded, that the colors which stimulate subject's alertness, awareness even are aggressive in some sort brought the best visibility, thus empowering the bias triggering message to be better seen, thus perceived better. This outcome could have been expected from the very beginning, as Aslam (2006) already had described the potential human reaction to particular colors. Numerous studies by Allagui & Lamoine (2008) were already proven that perception of colors in natural environment (described by Aslam (2006)) could be easily transferred to online environment and same behavior could be expected. The results of this research empirically prove the smooth transition of color perception in “real” life and in online environment. What is more, visual execution (colors) helped cognitive biases’ to perform better.

To summarize, unifying the theory and experiment results it can be stated, that cognitive biases could help webmasters or business owners online to make decision making for their customers faster and easier. What is more, in some cases cognitive biases assessment may even create a push for subjects to make a specific decision which favors already predefined business goals. To continue with, the message, tool or feature which assess the cognitive biases and triggers heuristic thinking of the subjects, should be well visible and to achieve that, bright colors with high saturation should be used, as they boost specific properties of human’s information perception, thus enhancing the effectiveness of cognitive biases which are in use.

4.3 Research Limitations

Several limitations could be pointed out in this research. First of all, during the experiment there was no control over the audience that was exposed to the cognitive biases and visual execution combinations. This means that people participating in the experiment may have had different willingness to purchase or simply were at different point in the customer cycle (for example, subject visits the site only to search for possible purchase for the evening. Once he or she decides, the purchase is made only later).

Secondly, the means of tracking customer behavior online could be improved. During this experiment only listed variables were tracked, however by enabling the platform to track affects cognitive biases and visual execution has on whole site globally, could provide more data and help to construct the relationship ties with better detail. For example, the behavior of returning customers, already pre-exposed to cognitive biases could have been taken into account.

Another possible weakness of this research and the experiment might be the overall exposure and coverage of cognitive biases and their visual execution throughout the platform. At the moment, only one site page was affected by the experiment, however, if the coverage of cognitive biases triggering messages would be implemented throughout the page, thus providing more consistency and possibly making the message more visible and increasing the overall effects on consumer behavior.

Finally, the experiment data was collected only over one week of time. Increasing the duration of the experiment could help collecting more data, thus implemented with previously mentioned improvements could provide even more and still untapped insights on cognitive biases and their visual execution impact on consumer behavior in e-commerce platforms.

4.4 Suggestions for Future Research

The main findings presented in this paper points out not only several possibilities of improvement, but also raises some questions for the future.

First of all, in this paper the assessment of cognitive biases was measured through very narrow set of variables representing only the cornerstone features of consumer behavior online: engagement, conversions, generated revenue. The employment of heuristic thinking in guiding individuals through each of the steps of customer lifecycle online could be one of possible fields of study. It is highly possible, that different cognitive biases provide different heuristic behavior, thus it could help to guide a possible client through each of the step and goal towards purchase and/or ultimate online platform goal in a faster, more efficient way. To add up, different means of visual execution should be examined as well, because different cognitive biases may require different visual communication. The optimal points of interaction should be examined beforehand.

What is more, in this paper only desktop device users were examined, because the platform on which experiment was conducted was not compatible with tablet and mobile devices. Alternative tests could be run on platforms compatible with broader types of devices to examine whether cognitive biases and their visual execution employment would have different effects for each device category.

To continue with, experiment in this research was carried out on all types of customers indistinctively. A more detailed analysis of cognitive biases and their visual execution effects on such customer segments as first time buyers and rebuyers could be examined.

5. Conclusions

The aim of this research was to examine what impact does cognitive biases and their visual execution has on consumer behavior in e-commerce platforms.

First of all, two big scholar movements were overviewed: cognitive biases and means of visual execution. The first was built on work off corner stone works by Amos Tversky and Daniel Kahneman. They were the first to introduce “cognitive bias” term in 1974. The idea behind, is that specific cognitive biases in human mind, may trigger heuristic thinking which relies on bounded rationality principles (Simon, 1955) (Tversky & Kahneman, 1974) (Wilke & Mata, 2012). In other words, by providing specific information in a specific way it is possible to manipulate human thinking and create a “push” for individuals so that they make decisions which satisfy already predefined goals. Biases, which could be executed online, were chosen. These were following: countdown effect, bandwagon effect, loss aversion and gain effect. Following the examples and historical experiments by Tversky & Kahneman (1974, 1991) the specific messages supposedly triggering cognitive biases were constructed. What is more, the effects of cognitive biases were measured online, where visual execution is one of the crucial ways of information provision (Allagui & Lamoine, 2008) (Alexander, 2006). The second portion of literature was analyzed, focusing on the means of visual execution online. Colors were chosen as one of the most important factors, as it could potentially provide the biggest impacts for biases' performance (Aslam, 2006) (Biers & Richards, 2005) (Jiang & Benbasat, 2004).

In order to empirically asses the interaction of the mentioned factors and check possible effects on subjects it was chosen to carry out an experiment in a working e-commerce platform. After evaluating the collected data the following conclusions can be made:

1. All four examined cognitive biases have a positive effect on customer engagement in e-commerce platforms. Exposure to cognitive bias lead to increased time spent on specific page and more page views during unique session on a webpage. This means that subjects were interacting with website content more when exposed to cognitive biases.
2. Based on empirical findings, Loss Aversion cognitive bias had the highest weighted mean scores for maximizing page views of ecommerce platforms; consequently Countdown Effect scored the best, when trying to maximize time spent on page. So ultimately, for higher view – through engagement Loss Aversion effect should be adopted and for engagement with one site – page countdown effect could be used.

3. Cognitive biases affect conversion rate positively. The pages which were equipped with cognitive biases had better conversion rates than those without. This indicates that it is possible to push subjects towards pre-defined business goals by triggering their heuristic thinking.
4. Out of the set of used cognitive biases, Loss Aversion performed the best in terms of overall conversions on e-commerce platform. Thus meaning, that in order to maximize site conversions, cognitive biases addressing loss aversion might perform the best.
5. Visual execution strengthens the effect of the cognitive biases. During experiment, cognitive biases equipped with red color scored better than their green counterparts. This means, that stimulating alertness and awareness of the subject helps to better see and perceive the message triggering cognitive biases. Consequently, it becomes easier to assess heuristic thinking and ultimately, guide subject towards the ultimate goal.
6. Colors, stimulating awareness, alertiveness and possessing high levels of brightness, hue and saturation provide the best visibility for the subjects. Cognitive biases equipped with visual execution dominated by red color showed the best performance in all sets of dependent variables, thus meaning that aggressive colors make the perception of message stimulating cognitive bias more effective, consequently making the access to the heuristic thinking easier.

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Appendices

Appendix 1. Experiment Matrix Table

<table>
<tr><th rowspan="2">Cognitive Bias</th><th colspan="2">Visual Execution</th></tr>
<tr><th>Red - #cd1d36</th><th>Green - #90c200</th></tr>
<tr><td>Countdown Effect</td><td>
</td><td>
</td></tr>
<tr><td>Bandwagon Effect</td><td>
</td><td>
</td></tr>
<tr><td>Loss Aversion</td><td>
</td><td>
</td></tr>
</table>

Gain/Loss		
CONTROL **- #55422e**		

Appendix 2. Session Distribution

Descriptive Statistics of Cognitive Biases and Visual Execution

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	.2711	.44509	380
	Total	.2711	.44509	380
Countdown	Red	.3047	.46082	443
	Green	.3018	.45959	434
	Total	.3033	.45995	877
Bandwagon	Red	.3437	.47550	419
	Green	.3183	.46637	421
	Total	.3310	.47084	840
Loss Aversion	Red	.3525	.47831	434
	Green	.3626	.48131	422
	Total	.3575	.47954	856
Gain Loss	Red	.3603	.48068	408
	Green	.3099	.46296	455
	Total	.3337	.47181	863
Total	Control	.2711	.44509	380
	Red	.3398	.47378	1704
	Green	.3227	.46766	1732
	Total	.3252	.46851	3816

Device Category

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Desktop	2641	69.2	69.2	69.2
	Tablet	152	4.0	4.0	73.2
	Mobile	1023	26.8	26.8	100.0
	Total	3816	100.0	100.0	

Appendix 3. Device Significance Testing

Group Statistics

	Device Category	N	Mean	Std. Deviation	Std. Error Mean
Page Value	Desktop	2641	7.444551	14.5158204	.2824603
	Mobile	1023	3.785809	8.1269284	.2540906
Pageviews	Desktop	2641	4.12	5.673	.110
	Mobile	1023	2.51	2.414	.075
Time on Page	Desktop	2641	107.41	269.417	5.243
	Mobile	1023	62.89	167.092	5.224
Conversion	Desktop	2641	.3658	.48174	.00937
	Mobile	1023	.2111	.40832	.01277

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Page Value	Equal variances assumed	94.399	.000	7.612	3662	.000	3.6587419	.4806284	2.7164161	4.6010678
	Equal variances not assumed			9.630	3210.590	.000	3.6587419	.3799287	2.9138145	4.4036694
Pageviews	Equal variances assumed	97.403	.000	8.815	3662	.000	1.617	.183	1.258	1.977

	Equal variances not assumed			12.096	3633.970	.000	1.617	.134	1.355	1.880
Time on Page	Equal variances assumed	40.001	.000	4.930	3662	.000	44.518	9.030	26.814	62.221
	Equal variances not assumed			6.015	2956.225	.000	44.518	7.401	30.006	59.030
Conversion	Equal variances assumed	457.582	.000	9.080	3662	.000	.15463	.01703	.12124	.18801
	Equal variances not assumed			9.763	2176.254	.000	.15463	.01584	.12357	.18569

Group Statistics

	Device Category	N	Mean	Std. Deviation	Std. Error Mean
Page Value	Desktop	2641	7.444551	14.5158204	.2824603
	Tablet	152	7.146513	9.8494723	.7988977
Pageviews	Desktop	2641	4.12	5.673	.110
	Tablet	152	3.10	2.513	.204
Time on Page	Desktop	2641	107.41	269.417	5.243
	Tablet	152	72.49	123.452	10.013
Conversion	Desktop	2641	.3658	.48174	.00937
	Tablet	152	.3882	.48894	.03966

Independent Samples Test

	Levene's Test for Equality of Variances	t-test for Equality of Means	
			95% Confidence Interval of the Difference

		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Page Value	Equal variances assumed	.658	.417	.250	2791	.803	.2980377	1.1929918	-2.0411977	2.6372730
	Equal variances not assumed			.352	190.941	.725	.2980377	.8473614	-1.3733538	1.9694291
Pageviews	Equal variances assumed	10.098	.002	2.215	2791	.027	1.025	.463	.118	1.933
	Equal variances not assumed			4.423	251.341	.000	1.025	.232	.569	1.482
Time on Page	Equal variances assumed	7.699	.006	1.588	2791	.112	34.922	21.987	-8.190	78.035
	Equal variances not assumed			3.090	244.079	.002	34.922	11.303	12.659	57.186
Conversion	Equal variances assumed	1.059	.303	-.557	2791	.578	-.02239	.04022	-.10124	.05647
	Equal variances not assumed			-.549	168.314	.583	-.02239	.04075	-.10284	.05806

Appendix 4. Two tailed ANOVA on dependent variables

Between-Subjects Factors

		Value Label	N
Cognitive Bias	0	Control	251
	1	Countdown	610
	2	Bandwagon	601
	3	Loss Aversion	600
	4	Gain Loss	579
Color	0	Control	251
	1	Red	1167
	2	Green	1223

Descriptive Statistics

Dependent Variable:Conversion

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	.3267	.46994	251
	Total	.3267	.46994	251
Countdown	Red	.3490	.47745	298
	Green	.3077	.46228	312
	Total	.3279	.46982	610
Bandwagon	Red	.3826	.48681	311
	Green	.3655	.48241	290
	Total	.3744	.48436	601
Loss Aversion	Red	.3926	.48915	298
	Green	.4106	.49276	302
	Total	.4017	.49064	600
Gain Loss	Red	.4385	.49716	260
	Green	.3260	.46949	319
	Total	.3765	.48493	579
Total	Control	.3267	.46994	251
	Red	.3890	.48774	1167
	Green	.3516	.47766	1223

Descriptive Statistics

Dependent Variable:Conversion

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	.3267	.46994	251
	Total	.3267	.46994	251
Countdown	Red	.3490	.47745	298
	Green	.3077	.46228	312
	Total	.3279	.46982	610
Bandwagon	Red	.3826	.48681	311
	Green	.3655	.48241	290
	Total	.3744	.48436	601
Loss Aversion	Red	.3926	.48915	298
	Green	.4106	.49276	302
	Total	.4017	.49064	600
Gain Loss	Red	.4385	.49716	260
	Green	.3260	.46949	319
	Total	.3765	.48493	579
Total	Control	.3267	.46994	251
	Red	.3890	.48774	1167
	Green	.3516	.47766	1223
	Total	.3658	.48174	2641

Tests of Between-Subjects Effects

Dependent Variable:Conversion

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.977[a]	5	.595	2.573	.025
Intercept	248.313	1	248.313	1073.178	.000
CognitiveBias	1.716	3	.572	2.473	.060
Color	.833	1	.833	3.600	.058
Error	609.689	2635	.231		
Total	966.000	2641			
Corrected Total	612.666	2640			

Tests of Between-Subjects Effects

Dependent Variable:Conversion

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.977[a]	5	.595	2.573	.025
Intercept	248.313	1	248.313	1073.178	.000
CognitiveBias	1.716	3	.572	2.473	.060
Color	.833	1	.833	3.600	.058
Error	609.689	2635	.231		
Total	966.000	2641			
Corrected Total	612.666	2640			

a. R Squared = .005 (Adjusted R Squared = .003)

Appendix 5. One-Way ANOVA on Cognitive Biases

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
Pageviews	Control	251	1.10	.624	.039	1.03	1.18	1	10
	Countdown	610	4.38	5.230	.212	3.97	4.80	1	64
	Bandwagon	601	4.51	6.870	.280	3.96	5.06	1	83
	Loss Aversion	600	4.64	6.248	.255	4.14	5.14	1	61
	Gain Loss	579	4.23	4.908	.204	3.83	4.63	1	38
	Total	2641	4.12	5.673	.110	3.91	4.34	1	83
Page Value	Control	251	6.474861	11.3061125	.7136355	5.069357	7.880365	.0000	76.8900
	Countdown	610	6.799419	15.5447009	.6293865	5.563388	8.035451	.0000	216.9336
	Bandwagon	601	8.079407	17.4867016	.7132974	6.678544	9.480270	.0000	212.8723
	Loss Aversion	600	8.085409	13.0401880	.5323634	7.039884	9.130935	.0000	97.5700
	Gain Loss	579	7.221509	12.5351690	.5209438	6.198335	8.244683	.0000	100.8083
	Total	2641	7.444551	14.5158204	.2824603	6.890685	7.998417	.0000	216.9336
Time on Page	Control	251	44.91	114.378	7.219	30.69	59.13	0	1013
	Countdown	610	123.05	308.580	12.494	98.51	147.58	0	3589
	Bandwagon	601	110.54	250.778	10.229	90.45	130.63	0	2225
	Loss Aversion	600	117.51	314.196	12.827	92.32	142.70	0	4252

	Gain Loss	579	104.31	236.380	9.824	85.02	123.61	0	2913
	Total	2641	107.41	269.417	5.243	97.13	117.69	0	4252
Conversion	Control	251	.3267	.46994	.02966	.2683	.3851	.00	1.00
	Countdown	610	.3279	.46982	.01902	.2905	.3652	.00	1.00
	Bandwagon	601	.3744	.48436	.01976	.3356	.4132	.00	1.00
	Loss Aversion	600	.4017	.49064	.02003	.3623	.4410	.00	1.00
	Gain Loss	579	.3765	.48493	.02015	.3369	.4161	.00	1.00
	Total	2641	.3658	.48174	.00937	.3474	.3842	.00	1.00

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Pageviews	Between Groups	2585.668	4	646.417	20.684	.000
	Within Groups	82378.844	2636	31.251		
	Total	84964.512	2640			
Page Value	Between Groups	1007.346	4	251.837	1.196	.311
	Within Groups	555264.523	2636	210.647		
	Total	556271.869	2640			
Time on Page	Between Groups	1202171.195	4	300542.799	4.160	.002
	Within Groups	1.904E8	2636	72239.369		
	Total	1.916E8	2640			
Conversion	Between Groups	2.144	4	.536	2.314	.055
	Within Groups	610.522	2636	.232		
	Total	612.666	2640			

Multiple Comparisons

Bonferroni

Dependent Variable	(I) Cognitive Bias	(J) Cognitive Bias	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Pageviews	Control	Countdown	-3.278*	.419	.000	-4.46	-2.10
		Bandwagon	-3.404*	.420	.000	-4.58	-2.22
		Loss Aversion	-3.538*	.420	.000	-4.72	-2.36
		Gain Loss	-3.123*	.422	.000	-4.31	-1.94
	Countdown	Control	3.278*	.419	.000	2.10	4.46
		Bandwagon	-.126	.321	1.000	-1.03	.78
		Loss Aversion	-.260	.321	1.000	-1.16	.64
		Gain Loss	.156	.324	1.000	-.76	1.07
	Bandwagon	Control	3.404*	.420	.000	2.22	4.58
		Countdown	.126	.321	1.000	-.78	1.03
		Loss Aversion	-.134	.323	1.000	-1.04	.77
		Gain Loss	.281	.326	1.000	-.63	1.20
	Loss Aversion	Control	3.538*	.420	.000	2.36	4.72
		Countdown	.260	.321	1.000	-.64	1.16
		Bandwagon	.134	.323	1.000	-.77	1.04
		Gain Loss	.415	.326	1.000	-.50	1.33
	Gain Loss	Control	3.123*	.422	.000	1.94	4.31

		Countdown	-.156	.324	1.000	-1.07	.76
		Bandwagon	-.281	.326	1.000	-1.20	.63
		Loss Aversion	-.415	.326	1.000	-1.33	.50
Page Value	Control	Countdown	-.3245587	1.0883712	1.000	-3.382228	2.733111
		Bandwagon	-1.6045464	1.0907443	1.000	-4.668883	1.459790
		Loss Aversion	-1.6105489	1.0910121	1.000	-4.675638	1.454540
		Gain Loss	-.7466484	1.0968321	1.000	-3.828088	2.334791
	Countdown	Control	.3245587	1.0883712	1.000	-2.733111	3.382228
		Bandwagon	-1.2799877	.8341558	1.000	-3.623465	1.063489
		Loss Aversion	-1.2859902	.8345059	1.000	-3.630451	1.058470
		Gain Loss	-.4220897	.8421006	1.000	-2.787887	1.943707
	Bandwagon	Control	1.6045464	1.0907443	1.000	-1.459790	4.668883
		Countdown	1.2799877	.8341558	1.000	-1.063489	3.623465
		Loss Aversion	-.0060025	.8375985	1.000	-2.359151	2.347146
		Gain Loss	.8578980	.8451655	1.000	-1.516509	3.232305
	Loss Aversion	Control	1.6105489	1.0910121	1.000	-1.454540	4.675638
		Countdown	1.2859902	.8345059	1.000	-1.058470	3.630451
		Bandwagon	.0060025	.8375985	1.000	-2.347146	2.359151
		Gain Loss	.8639005	.8455110	1.000	-1.511478	3.239279
	Gain Loss	Control	.7466484	1.0968321	1.000	-2.334791	3.828088
		Countdown	.4220897	.8421006	1.000	-1.943707	2.787887
		Bandwagon	-.8578980	.8451655	1.000	-3.232305	1.516509
		Loss Aversion	-.8639005	.8455110	1.000	-3.239279	1.511478

Time on Page	Control	Countdown	-78.135*	20.155	.001	-134.76	-21.51
		Bandwagon	-65.628*	20.199	.012	-122.38	-8.88
		Loss Aversion	-72.594*	20.204	.003	-129.36	-15.83
		Gain Loss	-59.400*	20.312	.035	-116.46	-2.34
	Countdown	Control	78.135*	20.155	.001	21.51	134.76
		Bandwagon	12.507	15.447	1.000	-30.89	55.90
		Loss Aversion	5.541	15.454	1.000	-37.88	48.96
		Gain Loss	18.735	15.595	1.000	-25.08	62.55
	Bandwagon	Control	65.628*	20.199	.012	8.88	122.38
		Countdown	-12.507	15.447	1.000	-55.90	30.89
		Loss Aversion	-6.966	15.511	1.000	-50.54	36.61
		Gain Loss	6.228	15.651	1.000	-37.74	50.20
	Loss Aversion	Control	72.594*	20.204	.003	15.83	129.36
		Countdown	-5.541	15.454	1.000	-48.96	37.88
		Bandwagon	6.966	15.511	1.000	-36.61	50.54
		Gain Loss	13.194	15.658	1.000	-30.79	57.18
	Gain Loss	Control	59.400*	20.312	.035	2.34	116.46
		Countdown	-18.735	15.595	1.000	-62.55	25.08
		Bandwagon	-6.228	15.651	1.000	-50.20	37.74
		Loss Aversion	-13.194	15.658	1.000	-57.18	30.79
Conversion	Control	Countdown	-.00118	.03609	1.000	-.1026	.1002
		Bandwagon	-.04768	.03617	1.000	-.1493	.0539
		Loss Aversion	-.07497	.03618	.383	-.1766	.0267

		Gain Loss	-.04982	.03637	1.000	-.1520	.0524
	Countdown	Control	.00118	.03609	1.000	-.1002	.1026
		Bandwagon	-.04651	.02766	.928	-.1242	.0312
		Loss Aversion	-.07380	.02767	.077	-.1515	.0039
		Gain Loss	-.04864	.02792	.816	-.1271	.0298
	Bandwagon	Control	.04768	.03617	1.000	-.0539	.1493
		Countdown	.04651	.02766	.928	-.0312	.1242
		Loss Aversion	-.02729	.02777	1.000	-.1053	.0507
		Gain Loss	-.00214	.02802	1.000	-.0809	.0766
	Loss Aversion	Control	.07497	.03618	.383	-.0267	.1766
		Countdown	.07380	.02767	.077	-.0039	.1515
		Bandwagon	.02729	.02777	1.000	-.0507	.1053
		Gain Loss	.02516	.02804	1.000	-.0536	.1039
	Gain Loss	Control	.04982	.03637	1.000	-.0524	.1520
		Countdown	.04864	.02792	.816	-.0298	.1271
		Bandwagon	.00214	.02802	1.000	-.0766	.0809
		Loss Aversion	-.02516	.02804	1.000	-.1039	.0536

*. The mean difference is significant at the 0.05 level.

Appendix 6. T-tests on cognitive biases & conversions

Group Statistics

	Cognitive Bias	N	Mean	Std. Deviation	Std. Error Mean
Conversion	Control	251	.3267	.46994	.02966
	Bandwagon	601	.3744	.48436	.01976

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Conversion	Equal variances assumed	7.881	.005	-1.321	850	.187	-.04768	.03609	-.11851	.02315
	Equal variances not assumed			-1.338	481.548	.182	-.04768	.03564	-.11771	.02235

Group Statistics

	Cognitive Bias	N	Mean	Std. Deviation	Std. Error Mean
Conversion	Control	251	.3267	.46994	.02966
	Loss Aversion	600	.4017	.49064	.02003

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Conversion	Equal variances assumed	20.414	.000	-2.058	849	.040	-.07497	.03643	-.14648	-.00347
	Equal variances not assumed			-2.095	487.665	.037	-.07497	.03579	-.14530	-.00465

Group Statistics

	Cognitive Bias	N	Mean	Std. Deviation	Std. Error Mean
Conversion	Control	251	.3267	.46994	.02966
	Gain Loss	579	.3765	.48493	.02015

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Conversion	Equal variances assumed	8.495	.004	-1.372	828	.170	-.04982	.03631	-.12109	.02145
	Equal variances not assumed			-1.389	489.002	.165	-.04982	.03586	-.12028	.02064

Group Statistics

	Cognitive Bias	N	Mean	Std. Deviation	Std. Error Mean
Conversion	Control	251	.3267	.46994	.02966
	Countdown	610	.3279	.46982	.01902

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Conversion	Equal variances assumed	.004	.947	-.033	859	.973	-.00118	.03523	-.07033	.06798
	Equal variances not assumed			-.033	465.591	.973	-.00118	.03524	-.07042	.06807

Appendix 7. Visual Execution ANOVA

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Pageviews	Control	251	1.10	.624	.039	1.03	1.18	1	10
	Red	1167	4.63	6.258	.183	4.28	4.99	1	83
	Green	1223	4.26	5.472	.156	3.95	4.56	1	64
	Total	2641	4.12	5.673	.110	3.91	4.34	1	83
Page Value	Control	251	6.474861	11.3061125	.7136355	5.069357	7.880365	.0000	76.8900
	Red	1167	8.035608	14.9085776	.4364161	7.179359	8.891856	.0000	212.8723
	Green	1223	7.079570	14.7079149	.4205696	6.254452	7.904689	.0000	216.9336
	Total	2641	7.444551	14.5158204	.2824603	6.890685	7.998417	.0000	216.9336
Time on Page	Control	251	44.91	114.378	7.219	30.69	59.13	0	1013
	Red	1167	114.14	274.117	8.024	98.40	129.88	0	4252
	Green	1223	113.81	285.575	8.166	97.79	129.83	0	3589
	Total	2641	107.41	269.417	5.243	97.13	117.69	0	4252
Conversion	Control	251	.3267	.46994	.02966	.2683	.3851	.00	1.00
	Red	1167	.3890	.48774	.01428	.3610	.4170	.00	1.00
	Green	1223	.3516	.47766	.01366	.3248	.3784	.00	1.00
	Total	2641	.3658	.48174	.00937	.3474	.3842	.00	1.00

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Pageviews	Between Groups	2615.817	2	1307.909	41.898	.000
	Within Groups	82348.695	2638	31.216		
	Total	84964.512	2640			
Page Value	Between Groups	806.621	2	403.311	1.915	.147
	Within Groups	555465.248	2638	210.563		
	Total	556271.869	2640			
Time on Page	Between Groups	1083396.731	2	541698.366	7.500	.001
	Within Groups	1.905E8	2638	72229.625		
	Total	1.916E8	2640			
Conversion	Between Groups	1.261	2	.630	2.719	.066
	Within Groups	611.405	2638	.232		
	Total	612.666	2640			

Appendix 8. Two-Way ANOVA on Pageviews

Between-Subjects Factors

		Value Label	N
Cognitive Bias	0	Control	251
	1	Countdown	610
	2	Bandwagon	601
	3	Loss Aversion	600
	4	Gain Loss	579
Color	0	Control	251
	1	Red	1167
	2	Green	1223

Descriptive Statistics

Dependent Variable:Pageviews

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	1.10	.624	251
	Total	1.10	.624	251
Countdown	Red	4.09	3.948	298
	Green	4.66	6.206	312
	Total	4.38	5.230	610
Bandwagon	Red	4.68	7.878	311
	Green	4.32	5.599	290
	Total	4.51	6.870	601
Loss Aversion	Red	4.68	6.401	298
	Green	4.60	6.103	302
	Total	4.64	6.248	600
Gain Loss	Red	5.15	6.047	260
	Green	3.48	3.571	319
	Total	4.23	4.908	579
Total	Control	1.10	.624	251
	Red	4.63	6.258	1167

	Green	4.26	5.472	1223
	Total	4.12	5.673	2641

Levene's Test of Equality of Error Variances[a]

Dependent Variable:Pageviews

F	df1	df2	Sig.
16.337	8	2632	.000

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + CognitiveBias + Color + CognitiveBias * Color

Tests of Between-Subjects Effects

Dependent Variable:Pageviews

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3053.818[a]	8	381.727	12.266	.000	.036
Intercept	30103.039	1	30103.039	967.288	.000	.269
CognitiveBias	37.891	3	12.630	.406	.749	.000
Color	88.956	1	88.956	2.858	.091	.001
CognitiveBias * Color	387.418	3	129.139	4.150	.006	.005
Error	81910.694	2632	31.121			
Total	129877.000	2641				
Corrected Total	84964.512	2640				

a. R Squared = .036 (Adjusted R Squared = .033)

Appendix 9. Two-Way ANOVA on Time on Page

Between-Subjects Factors

		Value Label	N
Cognitive Bias	0	Control	251
	1	Countdown	610
	2	Bandwagon	601
	3	Loss Aversion	600
	4	Gain Loss	579
Color	0	Control	251
	1	Red	1167
	2	Green	1223

Descriptive Statistics

Dependent Variable:Time on Page

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	44.91	114.378	251
	Total	44.91	114.378	251
Countdown	Red	98.74	188.209	298
	Green	146.26	389.266	312
	Total	123.05	308.580	610
Bandwagon	Red	116.31	286.471	311
	Green	104.36	206.069	290
	Total	110.54	250.778	601
Loss Aversion	Red	118.43	350.571	298
	Green	116.60	274.199	302
	Total	117.51	314.196	600
Gain Loss	Red	124.28	241.033	260
	Green	88.04	231.626	319
	Total	104.31	236.380	579
Total	Control	44.91	114.378	251
	Red	114.14	274.117	1167
	Green	113.81	285.575	1223

Descriptive Statistics

Dependent Variable:Time on Page

Cognitive Bias	Color	Mean	Std. Deviation	N
Control	Control	44.91	114.378	251
	Total	44.91	114.378	251
Countdown	Red	98.74	188.209	298
	Green	146.26	389.266	312
	Total	123.05	308.580	610
Bandwagon	Red	116.31	286.471	311
	Green	104.36	206.069	290
	Total	110.54	250.778	601
Loss Aversion	Red	118.43	350.571	298
	Green	116.60	274.199	302
	Total	117.51	314.196	600
Gain Loss	Red	124.28	241.033	260
	Green	88.04	231.626	319
	Total	104.31	236.380	579
Total	Control	44.91	114.378	251
	Red	114.14	274.117	1167
	Green	113.81	285.575	1223
	Total	107.41	269.417	2641

Levene's Test of Equality of Error Variances[a]

Dependent Variable:Time on Page

F	df1	df2	Sig.
5.741	8	2632	.000

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + CognitiveBias + Color + CognitiveBias * Color

Tests of Between-Subjects Effects

Dependent Variable:Time on Page

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	1.756E6	8	219545.467	3.043	.002	.009
Intercept	2.133E7	1	2.133E7	295.702	.000	.101
CognitiveBias	94629.132	3	31543.044	.437	.726	.000
Color	232.987	1	232.987	.003	.955	.000
CognitiveBias * Color	554192.092	3	184730.697	2.561	.053	.003
Error	1.899E8	2632	72138.596			
Total	2.221E8	2641				
Corrected Total	1.916E8	2640				

a. R Squared = .009 (Adjusted R Squared = .006)