ERASMUS UNIVERSITY ROTTERDAM

HOW DOES INFORMATIVE VERSUS PERSUASIVE ADVERTISEMENT INFLUENCE CUSTOMER INTENTIONS?

AN EYE TRACKING STUDY IN THE CONTEXT OF B2B EVENTS

Abstract

In this research paper, I examine the effect of different types of advertisement posters, namely informative and persuasive, on customer intentions towards business-to-business events. I conducted a laboratory experiment with 60 subjects, where I manipulated the type of advertisement posters and the level of uncertainty. I measured the level of attention that was paid to the posters with eye tracking technology. The results show indication that the level of uncertainty plays a moderating role, more specifically that subjects with a low uncertainty level are more positively influenced in their intentions by persuasive type of ads, whereas for subjects with a high uncertainty level, informative type of ads have a more positive impact on intentions. The mediating role of attention is examined as well, where I define attention as a combination of viewing time, number of fixations, gaze duration and average fixation duration. However, I did not find an indirect effect, and I concluded that attention does not play a mediating role in the relationship between type of poster and customer intentions. In the post-hoc analysis I did however find a significant interaction between level of attention and type of poster, indicating that when the level of attention is low, informative posters are more successful in increasing intentions, and when the level of attention is high, persuasive posters should be used. In the discussion, I make suggestions for B2B event advertising, and I discuss some limitations of the research.

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1. Introduction

1.1. The evolving landscape of advertising

Advertising is around us 24/7. When you walk to school, drive to work, listen to the radio or scroll through social media, you are exposed to advertising. As the world is more digitalized than ever, the way of advertising is evolving as well. There has been a significant transition from viewing traditional TV to connected TV (CTV), which refers to all TV programming that can be streamed over the internet. Advertisers leverage this shift, as according to Mediaocean (Lukovitz, 2022), 72% of marketers have expressed their intent to increase their ad spendings on CTV in 2022. Furthermore, eMarketer expects that CTV spendings will grow 20% each year in the coming four years (Lebow, 2022). This transition towards digital advertising is currently taking place and has already started as in the United States in 2021, 72% of the advertising budget was already allocated towards digital advertising (Lashbrook, 2022).

It is evident that the marketing and advertising landscape is evolving. According to the Marketing Science Institute, one of the top research priorities in 2020 – 2022 is the evolving landscape of Martech and Advertising, and more specially raises the question as to what “the optimal ad” is (MSI, 2020).

The process of designing the “optimal ad” depends on a lot of different factors, such as the industry of the product being advertised, the intended place the advertisement is shown, and the intended role of the ad. In literature, a clear distinction is made between two main effects of advertising, also referred to as the “roles of advertising”: an ad can have an informative role (i.e., an indirect effect) or an ad can have a more persuasive role (i.e., a direct effect) (Narayanan et al., 2003 & 2005).

In turn, this effect may vary across different customers, depending on their uncertainty level or what stage of the decision-making process they are in (Stankevich, 2017). For instance, customers that frequently purchase products from a particular brand are already familiar with the brand and evaluated the different alternatives. In that case, advertisements will have a less informative role, but customers still require to be persuaded by the ad. On the contrary, customers that are in the initial decision-making stages seeking information will be more informed by an ad.

These different effects and the relationship with uncertainty levels is well researched in literature (Narayanan et al., 2003 & 2005; Ackerberg, 2001). Research suggests that when the uncertainty level is high, advertisements often have an informative role, whereas when the uncertainty level is low, advertisements fulfill a more persuasive role.

It is worth noting that in the study by Narayanan et al. (2003 & 2005), the same advertisement was used throughout the various stages of the product life cycle, while the uncertainty levels varied as well (low and high uncertainty). However, advertisers often are able to modify the advertisement poster according to the uncertainty level of their customers. The influence of such modifications can be researched as well. It raises the question what the effect of different types of advertisement posters would be on customer intentions towards a particular product or brand.

1.2. The B2B industry

The field of advertising has been extensively studied: the different roles of advertising, the influence of the uncertainty level, as well as the role of attention, which is further explored in this paper as well. However, the majority of this research focuses on product advertising, while services remain an under-researched market, despite their contribution of more than 70% to the GDP (Statista, 2023; Escip, 2014). Furthermore, the greater part of the existing literature studies within the B2C (business-to-consumer) context, leaving the B2B (business-to-business) industry relatively unexplored, also referred to as the "B2B knowledge gap" (Lilien, 2016). Interestingly, according to Statista, B2B e-commerce sales in the United States in 2022 were much larger than B2C e-commerce sales, USD 1.8 trillion and USD 875 million, respectively (Dopson, 2022).

Given that the B2B service industry is relatively under-researched in advertising research, it provides an interesting research opportunity. One of the key marketing channels in the B2B service industry are B2B events, as marketeers often sponsor fairs or organize other events like workshops or launches to increase brand recognition (Eira, 2022). Although B2B events play in important role in marketing strategies, which is also be explained more in chapter three, it is not too often studied and for that reason, this paper specifically focuses on the advertising of events in a B2B context.

With that being said, the goal of this research paper is to find an answer to the question:

"How do different types of advertisements (informative versus persuasive) affect customer intentions towards business-to-business events?"

To help find an answer to the research question, the following sub questions are answered in this research paper as well:

1. *What different types of advertisements are there?*
2. *What makes an advertisement poster informative and/or persuasive?*
3. *How is it possible to measure customer intentions, and are customer intentions always truthful?*

4. *Is the effect of advertisement posters on customer intentions depending on the uncertainty level of the customer?*
5. *Does the level of attention towards an ad play a mediating role in the relationship between the advertisement poster and customer intentions?*

1.3. Conceptual and Empirical Approach

To answer this research question, the present study aims to investigate the effect of different advertisement posters (informative and persuasive) on the intentions subjects have towards the B2B event, i.e., how likely the subjects would be to the attend the event.

The paper by Narayanan et al. (2005) shows that the level of uncertainty can affect the manner in which advertisement posters impact customer intentions. Depending on the uncertainty level of the customer, advertisements can serve either a more informative or persuasive purpose. This relationship is addressed in sub question 4.

An additional element that may impact the relationship between advertisement posters and customer intentions is the level of attention a customer pays to the poster. Prior studies have identified a positive correlation between the attention paid to an ad and the evaluation of the ad (Maughan et al, 2007; Lee & Ahn, 2014). As various posters attract differing levels of attention, this could in turn influence customer intentions, which is addressed in sub question 5.

To find answers to the sub questions, an experimental study is conducted. Different posters for various B2B events are designed, both informative and persuasive. Participants are presented with four different posters, each advertising a different event. To examine the moderating role of uncertainty, participants are manipulated in their uncertainty level before they view the advertisement posters. The experiment follows a complete within subject design, such that all participants are presented with two informative posters and two persuasive posters, while experiencing a high level on uncertainty twice, and a low level twice.

To study the mediating role of attention, eye tracking is used as a measure for attention. The experiment is conducted in the Erasmus Behavioral Lab, which facilitated the use of an eye tracking device. Eye tracking has proven to be a good measure for attention, as it overcomes the limitations of self-reported data (self-reported bias, Scott et al., 2016).

1.4. Research contribution

This research paper makes several contributions to the existing literature. Firstly, it adapts the concept introduced by Narayanan et al. (2003 & 2005) and combines it with the Consumer decision making model, where uncertainty levels differ and play a role in the relationship between advertising and customer intentions. This is applied to the B2B events industry, an area that has received little research attention.

Rather than examining what role the advertisement fulfills, informing or persuading, this study manipulates the actual advertisement posters to assess the effect of different types of posters on customer intentions, depending on the uncertainty level of the customer. Based on literature, I expect that for customers with a low uncertainty level, persuasive posters have a more positive impact on intentions, while for those with a high uncertainty level, informative posters a more effective in increasing customer intentions.

Furthermore, this study adds to the literature by exploring the mediating role of attention, measured through the use of eye tracking, which helps to overcome self-reported bias. Although eye tracking has been used before as a measure for attention, it has not yet been applied in the B2B events industry, nor while manipulating both the type of advertisement poster as well as the uncertainty level of the customer in the same study.

Thus, this research paper combines multiple theories from literature and applies them to an under-researched industry, providing a valuable contribution to the existing literature.

1.5. Summary of Results

Two elements were manipulated in this experiment: the uncertainty level and the type of poster. The manipulation of the type of poster was successful (and significant), as subjects that viewed an informative poster within a certain trial indicated that they felt more informed compared to subjects that saw a persuasive poster within a certain trial. The manipulation of the uncertainty level was successful as well to an extent. However, the difference was very small and not significant (even though approaching significance, $p = 0{,}149 < 0{,}15$)

After performing the analyses, interesting results were found. In general, regardless of the uncertainty level of the subject, seeing a persuasive poster significantly decreased the intentions of the subject compared to the identical subject who saw an informative poster.

However, there was an interaction between the type of poster and the uncertainty level of the subject. When the uncertainty level was low, the persuasive posters had a (slightly) more positive effect on intentions than the informative posters, while for subjects with a high uncertainty level, the informative posters had a much more positive effect on intentions. Despite some indication of moderation, the coefficient of the interaction was not significant, and hypotheses 1A and 1B could not be formally supported.

The results did not show a mediating effect of attention, because no indirect effect was found. In other words, the effect of type of poster on customer intentions did not run through the attention level. Therefore, hypothesis 2 could not be supported.

However, a significant moderating effect of attention was found in the post-hoc analysis. Subjects that paid relatively much attention to the poster, were more positively influenced by a persuasive poster than an informative one, whereas subjects with a relatively low attention level were more positively influenced in their intentions by an informative poster rather than a persuasive one. Finally, I found that the textual element captured more attention than the visual element, contradicting most existing literature.

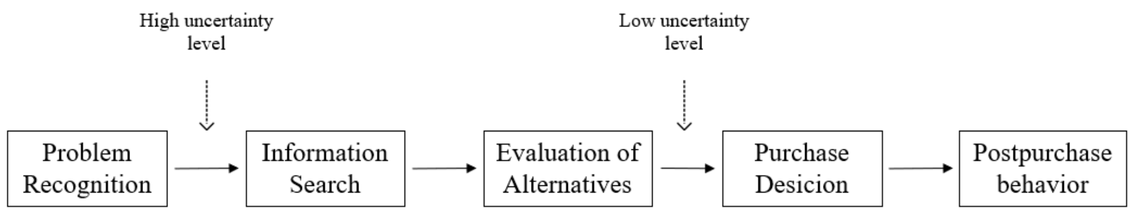
2. Literature review

2.1. Consumer Decision Making Process

Prior to making an actual purchase, people go through various stages in their decision making. These stages are summarized in the Consumer Decision Making and Purchasing Process (Stankevich, 2017). To review the literature, as well as build my hypotheses, I will anchor on the consumer decision making and purchasing process, as outlined in Figure 1.

Note that I am well aware that this model is originally a B2C model, and that it might be confusing that I apply these concepts to a B2B study. However, a customer within the B2B event industry goes through similar steps as a consumer in the B2C industry while deciding, as it is still an individual making the decision to go to an event or not, it is not the company that decides. This is also explained in the paper by Goldfarb et al. (2012), where it is explained that managerial decisions in a B2B context are often made by individuals and therefore many behavioral science models apply to the B2B context as well. Therefore, it is justified to use the model of the Consumer Decision Making Process (a B2C model) and apply it in the B2B event industry. However, I use the term customer instead of consumer in the discussion.[1]

Figure 1: Conceptual model of the Consumer Decision Making Process (Stankevich, 2017)



Multiple variants of this process have been published, some with more than 5 steps, and others based on the internal psychological processes (Belch & Belch, 2004). But in general, the process starts by recognizing that there is a need for something, followed by the customer searching for information about the product or service. Upon evaluating the alternatives that are available, the customer will come to decision whether to proceed to a purchase or not. Subsequently, after the purchase, the customer's post purchase behavior may include the determination of their satisfaction, and potentially lead customer loyalty and repurchases in the future.

[1] In a B2B context, the term "customer" is often more appropriate than the term "consumer", as a consumer is the end user of a product, which is not the often case in B2B. I explain this more elaborately in section 3.4

The figure illustrates that customers go through different levels of uncertainty in this decision making and purchasing process. Initially, when the need or problem is recognized, the level of uncertainty is high, as the customer is not yet familiar with the different alternatives because no information search has taken place yet. As the process continues, when all alternatives are evaluated and the customer is moving towards a purchasing decision, the uncertainty level decreases as the customer is aware of the differences between brands and products.

Undoubtedly, advertisements can help customers during this decision making and purchasing process. For instance, advertisements can enhance brand awareness, which is particularly crucial before and during the information search stage. On the other hand, advertisements can also aim to persuade customers that their brand or product is superior to the competition, which is more relevant during the stage of evaluation of the alternatives, where the uncertainty is lower. In other words, the role that advertising fulfills depends on the stage in the decision making process, as the degree of uncertainty of the customer varies throughout the stages. In literature, this is referred to as the "role of advertising".

2.2. The role of advertising

Existing literature distinguishes two primary roles of advertising, namely the informative role and the persuasive role, or in some papers also referred to as the direct and indirect effect of advertisement (Narayanan et al., 2003 & 2005). These studies suggest that when the uncertainty level is high, advertising often fulfills a more informative role, whereas when the uncertainty level is low, advertising can have a more persuasive effect.

While the informative role of advertising is quite well defined in the literature, there are multiple inconsistencies and competing definitions regarding the persuasive role of advertising. I will briefly review the literature, from the perspective of both these definitions.

The informative role of advertisement (i.e., the indirect effect of advertising) is primarily focused on reducing uncertainty a customer might have. In essence, prior scholars see advertising as a source of information that helps customers learn about desirable characteristics of a brand or product from exposure to such "advertising signals". The advertisement provides information about a product, which updates the belief of the customer and through a learning process, the uncertainty of the customer is reduced (Erdem & Keane, 1996). The research conducted by Narayanan, Manchanda and Chintagunta (2003 & 2005) found the effect of informative advertising is strongest with customers that have a relatively high level of uncertainty. This means that the customer is unfamiliar with the product, either because the product is still in the early stages and therefore not know by the public, or

because the customer has not heard of the product until then (before the information search in the Consumer Decision Making Process, Figure 1).
Opposite to informative advertising, we find persuasive advertising, also known as the ¨direct effect of advertising¨. This role of advertising is convoluted, as there are many different definitions available in literature. Essentially, the direct effect captures all effects that are not indirect, and therefore do not aim to reduce customer uncertainty. Generally, the indirect effect of advertising occurs more frequently when customers have a low level of uncertainty, i.e., in the later stages of the consumer decision making process. This is because such customers do not require additional information, as they already have the information they need about the product. In such cases, advertisement has a strong persuasive role and not so much an informing role.

Of course, an effect that captures all effects but reducing uncertainty is quite broad. In Table 1, an overview is provided of some highly rated papers and their perception or definition on both the informative and persuasive role of advertising.

Table 1: Literature overview informative and persuasive advertisement

	Title	Authors (Year)	Research direction	Definition of persuasive and informative advertisement	Summary of findings	Related papers
1	Advertising as information	Philip Nelson (1974)	The function of information in advertisements, depending on type of good (search goods with clear search attributes or experience goods where attributes are vaguer).	The role of advertisement depends on the type of good. Search goods: information itself is valuable for customer and that increases their utility → **informative advertisement** Experience goods: perception of the product changes because the brand advertises it in the first place (indirect/prestige effect) → **persuasive advertisement**	Information in advertisement can have a direct and indirect effect on customer's utility. For search goods, purely information increases their utility, whereas for experience goods, the ad itself increases their utility because of the fact the brand advertises.	Milgrom & Roberts (1986)
2	Repetitive advertising and the consumer	Andrew Ehrenberg (2000)	A model is proposed that criticizes AIDA (Attention, Interest, Desire, Action). AIDA has two roles of advertising (informative and persuasive), Ehrenberg's model ATR (Awareness, Trial, Reinforcement) has only one; helping customers to repurchase the product.	The focus lies on the persuasive role of advertising, informative advertising is not explicitly defined. **Persuasive advertisement:** explained as repetitive advertising where ad serves as reinforcement (reminder effect) and persuades them to repurchase the product. Advertisement can also serve to remind the customer to do a trial purchase, in order to create a purchase habit. This is also a reminder effect.	The purpose of advertising is to reinforce the satisfaction from a previously purchased good. Advertising serves as a reminder and tries to increase the number of repetitive purchases. It can also serve as a reawakening of brand awareness and to set customers to a trial purchase. This insight holds mostly for highly competitive goods (homogenous goods), where advertisement convinces customers of the superiority of their product compared to the competition (combative advertising)	Ambler (2000)
3	Empirically Distinguishing Informative and Prestige Effects of Advertising	Daniel Ackerberg (2001)	The different effects of advertisement of non-durable, experience goods on different types of customers (unfamiliar/high uncertainty level vs. familiar/low uncertainty level. Expected that inexperienced customers are affected by information, experienced by prestige.	**Informative advertisement:** goal to inform customers by providing information about the product. **Persuasive advertisement:** customers get persuaded because of the fact that the brand advertises (prestige or image effect). A product most be worthy because it is advertised, that is what creates prestige and increases utility.	The paper found a significant informative effect on inexperienced customers with a high uncertainty level. The paper did not find a significant persuasive effect, meaning that the ad did not cause a prestige or image effect, neither on experienced nor inexperienced customers.	Stigler & Becker (1977) and Becker & Murphy (1993)

4	Temporal differences in the role of marketing communication in new product categories	Sridhar Narayanan, Puneet Manchanda & Pradeep Chintagunta (2005)	The role of marketing communications (i.e., detailing) in the pharmacy industry, where a new product is advertised through various stages and the level of uncertainty of the customer varies.	**Informative advertisement:** indirect effect, with the goal to reduce uncertainty. **Persuasive advertisement:** direct effect, all non-indirect effects that influence preferences through goodwill accumulation (e.g., reminder effects or prestige effects).	Evidence was found for both the direct and indirect effect. In the preliminary stages (introductory stage, high level of uncertainty), more evidence for indirect effect and behavior changes because detailing is informative. In the later stages (less uncertainty), direct effect is more visible and behavior changes because of persuasion. The shift between informative and persuasive is caused by a learning process, reducing uncertainty levels.	
5	A theory of combative advertising	Yuxin Chen, Yogesh Joshi, Jagmohan Raju & John Zhang (2009)	Advertising as combative marketing and its effect on market power. In highly competitive markets, this can lead to price wars, which affects demand volume. A laboratory experiment where the effect of combative advertising on customer preferences is researched.	**Informative advertisement:** advertising that increases customer awareness and reduces search costs for the customer. **Persuasive advertising:** defined as combative advertising, where the goal is to shift the customer´s preferences from the competition to your brand. The ad persuades customers by telling them their brand is better than the competition.	Combative advertising can have a positive effect for all competing firms, when awareness in increased and the number of customers increases. This happens often when customers are responsive (to advertising). However, with non-responsive customers, combative advertising will probably lead to a price war, price reductions and it will disadvantage all competing firms.	Marshall (1919)
6	Advertising, the matchmaker	Bharat Anand & Ron Shachar (2011)	A study about television shows in the US on how advertisement can help matching customers with shows that are best suitable for them by informing them about different product attributes.	Although the paper mainly focuses on informative advertisement, it is possible to distinguish different effects of advertisement. **Informative advertisement:** the effect of obtaining information about product attributes to optimize the match between product (in this case show) and customer. **Persuasive advertisement:** defined as a direct effect where because of firm behavior (the fact that they advertise), the perception of the product changes (prestige effect).	Evidence is found that advertising can have a purely informative role, i.e., by informing customers about different attributes, the match between customer and products is optimized. The paper distinguishes two effects of providing information. On the one hand, utility increases directly because there is advertised (i.e., prestige/persuasive advertising) but utility also increases indirectly because information optimizes the match between customer and product (i.e., informative advertising by reducing uncertainty).	Erdem & Keane (1996) and Galbraith (1976)

The table shows that there are multiple ways literature defines persuasive advertising, and that, contrary to informative advertising, there is not a unified definition. If you want to categorize the various definitions of persuasive advertising, the two main categories would be prestige effects and reminder effects.

The prestige effect captures the effects caused by the fact a product or brand is being advertised in the first place. It suggests that a product most be worthy of buying, because otherwise the company would not pay money for advertising. The perceived value of a product or brand increases which in turn increases purchase intentions (Ackerberg, 2001; Stigler & Becker, 1977; Becker & Murphy, 1993; Anand & Shachar, 2011; Galbraith, 1976; Nelson, 1974).

The reminder effect is the result of advertising that helps to remind a customer either of a previous experience to reinforce the satisfaction they experienced, or to remind a customer of an existing product to convince them to make a trial purchase that can lead to a future purchase habit (Ehrenberg, 2000; Ambler, 2000).

There are also some scholars that mention emotional advertising, which can loosely be mapped into persuasive advertising as well. Emotional advertising often plays on the emotion of a customer and tries to link the product or service with the needs of the customer Teichert et al., 2018; Jang et al., 2014).

To summarize, the literature on the two roles of advertising, informative or persuasive advertising, is ambiguous. While there is a very clear definition of informative advertising, persuasive advertising captures multiple different effects like prestige and reminder effects. A unified definition of "persuasive" advertising offers an interesting research direction, however, as this is an empirical study, the goal of this paper is not to look for a unified definition. With that being said, in this paper I use the insights from existing literature and apply them in practice to examine the effect of persuasive and informative types of advertisements on customer intentions, and how effective these types of ads are dependent of the uncertainty level of the customer.

2.3. From "roles" to "types" of advertisements

As explained, marketing scholars have done a lot of research on the roles and effects of advertising. Different uncertainty levels (and different stages in the consumer decision making process) make advertising have a more informative role or persuasive role. A lot of this research is theory focused, and what marketeers ultimately need is information that can applied in practice. Because different uncertainty levels may require and ask for different types of ads, and often, marketeers are able to adapt their ads based on the uncertainty level of their targeted customers.

Therefore, it is important to translate the theory that is already known in literature about roles of advertisements and apply this to different types of advertisements, which can be informative or persuasive, in order to make actual suggestions that can be applied in practice. And that is exactly what I will do in this paper.

2.4. Attention as a factor

In addition to the role uncertainty plays in the effectiveness of advertisements, there are other factors involved that influence the adaptation and effectiveness of an ad. One of those factors is the level of attention the ad captures, as an advertiser, reaching your target audience is one thing, but capturing and maintaining their attention is another.

Existing literature has previously examined the relationship between attention and advertisement effectiveness. Maughan et al. (2007) found that a positive relationship between attention to an ad and the evaluation of the ad, and Lee and Ahn (2014) found that the more attention is paid to an ad, the more favorable the attitude towards the brand gets.

Pieters & Wedel (2004) assessed the effect of type of advertisement on the level of attention paid to the ad and found that the attention paid to a poster was significantly different between the types of ads that were used.

Goodrich (2011) combines these two research directions, as he conducted a study that not only examined the relationship between attention and purchase intention (and brand attitude), but also explored the effect of type of ads on attention level. He found that the level of attention may depend on the type of ad, where in his study, pictorial ads captured more attention than textual ads. Additionally, the results showed a positive relationship between attention and both ad recall and purchase intention (and a negative impact on brand attitude). Conclusively, he found that while the type of ad can influence attention, attention can influence customer intentions or attitudes.

2.5. Key elements in advertisement posters

It has been established in the previous section that as an advertiser, capturing attention is crucial. Literature shows that in general, certain elements within an advertisement are more successful in capturing attention than others. For a company, it is important to determine what elements play a key role in their ads, as advertising can be costly and ad space is limited.

The study by Pieters & Wedel (2004) identified three key elements in static, printed ads: brand, picture and text. The brand element includes all visual information connected to the brand, like name and logo. The pictorial element covers all non-textual information except for brand pictures, and the textual element includes all textual information apart from brand text. Through eye tracking, the study showed that the pictural element is most effective in capturing attention to the ad as a whole, while the brand element is the best in transferring attention to the different elements. The textual element captures more attention the larger the text surface is, and this confirms the general belief that in advertising, size matters (Legge & Bigelow, 2011; Paquin et al., 2021).

In a study by Ryu et al. (2009), five key elements were determined: body text, head text, brand logo, product image and human model image. In general, pictorial elements captured more attention (more looking time and more fixations) than textual elements, however per unit size the textual elements received more fixations and looking time than the pictorial elements. The “general” finding that pictures capture more attention than textual elements is supported by multiple studies (Childers, 1986; Decrop, 2007; Scott et al., 2016).

In conclusion, brand logo, picture and text are the key elements in advertising, where in general, pictures capture more attention, however the textual element fulfills an important role as well, which is transferring information. These findings provide some grounds for the design of the posters in the experiment, and also allows me to form expectations when I test what elements capture the most attention in the experiment (Post-Hoc Analysis).

3. Research background: Advertising in B2B

3.1. Focus on Business to Consumer instead of Business to Business

Until now, the discussion had focused on the relationship between different types of ads and customer intentions, and the role of uncertainty and attention in this context. However, these elements have been discussed in a rather general matter, overlooking the fact that in literature, some industries have received more research attention than others.

The existing literature about advertising has dominant focus on the business-to-consumer (B2C) industry, while less attention is paid to the business-to-business (B2B) industry, which had led to what is commonly referred to as the "B2B knowledge gap" (Lilien, 2016). Despite the fact that B2B transactions are a big part of total transactions, little research has been done in the field of B2B advertising. Until the 21st century, there was little to no academic research available about B2B marketing in the top 4 marketing journals[2].

A study conducted by Pulizzi & Handley (2016) specifically focused on B2B content marketing (B2B CM), which is defined as "a set of strategies to distribute and deliver valuable content to your target audience to attract, engage, and generate new leads and customers while retaining existing ones" (Deshpande, 2020). The study, which distributed a survey amongst 1102 B2B marketers, found that of the 89% that use content marketing for their B2B marketing, 88% considered it an important part of their program. The results of this study show the importance of B2B marketing.

Research conducted by Stefan Wuyts and Gary Lilien emphasize the importance of further B2B marketing research as well, for example in the field of governance, digital and sustainability (Wuyts, 2021; Lilien et al., 2022).

3.2. Focus on products instead of services

Another interesting fact is that in advertising literature, services are typically less well researched than products, which is remarkable, as the service industry accounts for more than 70% of GDP (Statista, 2023). What makes services different from products is that per definition (with few exceptions), products are tangible, and services are intangible. And precisely due to the intangible qualities of services, it is more challenging to communicate and sell them (Mittal, 1999).

[2] Journal of Marketing, Journal of Marketing Research, Marketing Science and Journal of Consumer Research.

Even though the literature is limited, some research has been conducted on the advertisement of services. A study by Stafford and Day (1995) researched the difference between rational and emotional advertising for retail services, and found that in general, rational appeals generate a more positive attitude than emotional appeals. Sel and Aktas (2019) researched the evolution of the advertising posters of the Cannes Film Festival and found that between 1946 and 2016, the visual elements of the advertising posters became more and more important compared to the textual elements. In Appendix A, Figure 7, a collection of posters can be found where the shift from textual to visual elements between 1951 and today becomes clear.

3.3. The size of the industry

The absence of research on B2B marketing and advertising, in combination with the little academic studies available about the advertising of services, makes advertising of B2B services a particularly neglected area of research and therefore an area that is interesting to research further.

The lack of available academic research is surprising when you take in the massive size of the industry. For instance, the global B2B Service Review Platform Market (platforms that help other companies make optimal purchase decisions, for example websites that rate various B2B software programs) was valued at 197 million US dollars in 2021 and is forecast to grow to almost 900 million US dollars in the coming 10 years (*B2B Services Review Platforms Market*, n.d.).

A big part of B2B marketing is organizing in-person events. Research has shown for 73% of all companies, organizing these events are a key part of their B2B marketing strategy (Eira, 2022). Examples of B2B events are conferences, fairs and workshops, and are a big part of the B2B service industry. The importance of these events, combined with the scale of the B2B service industry, make B2B events an interesting research direction.

3.4. ¨Consumer¨ versus ¨Customer¨

As I focus on the B2B event industry, it is important to realize that even though events are organized for businesses, the company or person attending the event is often not the end user of a service. Often in B2B, the life cycle of the service continues and might be transferred to another person.

As an example, imagine there is a company that organizes a fair for products and services that are used in the public space, like playgrounds and city lighting. Companies present their products or services at this fair, and municipal officials go to this fair to find new potential suppliers for the public space of their town or city. In this situation, the municipal officers are not the end users of the product or service, those are the people that live in the city or town. This makes the municipal officials not the end-user, and therefore should be referred to as a “customer” and not a “consumer”.

More generally, a consumer is considered the end user of a product or service, despite whether they have actually purchased the product. On the other hand, a customer is someone who purchases a product of uses a service, but it not always the end user (Bhadoria, 2023). Because in this paper, the focus lies on B2B events, I only speak of customers, and not of consumers.

4. Hypotheses development

Based on the Consumer Decision Making and Purchasing model, and the different levels of uncertainty the customer goes through, I have argued that these different uncertainty levels ask for different types of advertisements. As a result, I have formed my research question which is the following:

"How do different types of advertisements (informative versus persuasive) affect customer intentions towards business-to-business events?"

To answer this research question, I examine the effect that different types of advertisements have on customer intentions. I break this research question down in two sub-questions, as also introduced in the introduction as empirical questions:

- For which uncertainty level does persuasive advertising have a stronger effect, and in which conditions does informative advertising have a stronger effect on customer intentions?
- What is the process through which informative and persuasive advertising influence customer intentions? Is it driven by attention?

4.1. Advertisement Type and Intention: The Moderating Role of Customer Uncertainty

My first sub-question focuses on a contingency view of the effectiveness of persuasive versus informative advertisements, i.e., in which conditions is persuasive advertisement more effective in shaping customer intentions than informative advertisement, and vice versa.

Prior literature typically shows that, in general, advertisements with a persuasive objective often have a more positive effect on customer intentions than similar ads that are informative in nature (Ehrenberg, 2000; Ambler, 2000).

However, these conclusions are not generalizable for every situation. A study conducted by Narayanan, Manchanda and Chintagunta (2005) followed the introduction of a new type of drug and tested the effect of advertising throughout the different stages of the products life cycle. What they found was that for newly introduced products, that are in the early stages of their product life cycle, advertising fulfilled a more informative role as it stimulated the product's uptake as physicians were not yet familiar with the product (the uncertainty level was high). After a while, the uncertainty level decreased, as the physicians became familiar with the product. The study found that in these later stages, advertising had a more persuasive effect. The advertisement remained the same throughout the experiment, but the effect of it was different. Other comparable studies (e.g., Ackerberg, 2001) suggest as well that the effectiveness of advertisements (informative versus persuasive) may depend on the level of uncertainty.

This is also what I hypothesize in this research, however because I am doing an experiment, I can manipulate both the advertisements (their content) and the uncertainty levels. Therefore, I speak of different advertisement types and not about roles or effects, as already explained in section 2.3. Following up on this, I have formulated two hypotheses that challenge the moderating role of uncertainty level, from two different angels:

Hypothesis 1A: *For customers with a relatively low uncertainty level, persuasive types of advertisements have a stronger positive impact on customer intentions compared to informative advertisements*

Hypothesis 1B: *For customers with a relatively high uncertainty level, informative types of advertisements have a stronger positive impact on customer intentions compared to persuasive advertisements.*

4.2. Advertisement Type and Intention: The Mediating Role of Attention

The second sub-question focuses on the process through which different types of ads influence customer intentions, and whether it is driven by attention. The relations that are explored are two-fold, as I test whether the type of advertisement influences the level of attention, and in turn whether the level of attention has an effect on customer intentions.

As explained in the literature review, different types of ads can influence the attention that is paid to the ad. Pieters & Wedel (2004) found that pictorial ads capture more attention than textual ads, and a study by Nilsson (2006) explains that a more difficult task, or a more complex type of advertisement, put more pressure on cognitive resources and leads to a lower level of attention. To the contrary, less complex types of ads release the cognitive resources which leads to a higher level of attention.

Secondly, plenty of literature provides evidence that there is a relationship between attention and intentions, evaluation of the ad, or attitude towards the ad. Maughan et al. (2007) and Lee & Ahn (2014) found a positive relationship between attention and evaluation and attitude towards the ad. Boscolo et al. (2021) found that for masculine types of ads, male visual attention and their relative attitudes towards the ads were correlated.

Goodrich (2011) already combined these two relationships into one study and found evidence for 1) the relationship between advertisement type and attention (pictorial ads captured more attention than textual) and 2) a positive relation between attention and purchase intentions. Before Goodrich, Pechmann and Stewart (1990) also used different ads in their study by varying the level of comparative claims and tested the effect on attention and purchase intentions. They found that "direct comparative claims attract attention and thereby enhance purchase intentions", which means that evidence was found for both relations and implies that attention acted a mediator in the relationship between the different ads and purchase intentions.

Although these studies were conducted in different fields, it provides plenty of ground to explore the mediating role of attention in the relationship between type of ads and intentions towards B2B events. Therefore, the second hypothesis is:

Hypothesis 2: *The effect of different types of advertising on customer intentions towards B2B events is mediated by customer attention.*

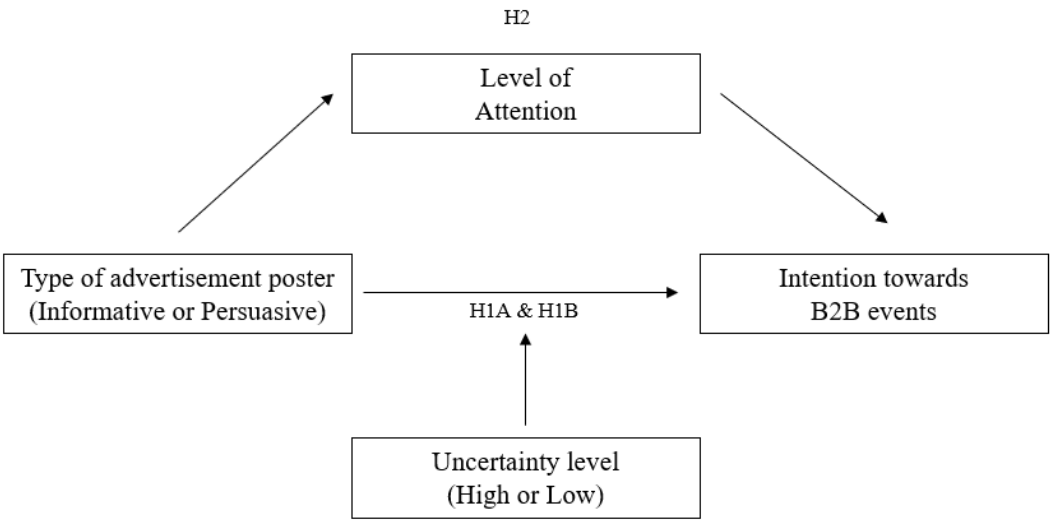
In the methodology section, I explain how attention is measured through eye tracking and that this is a valid measure for attention in order to overcome the problem of self-reported bias.

A summary of the hypotheses can be found in Table 2 and are graphically represented in the empirical model (Figure 2). The type of advertisement is the independent variable, intention of the customer towards B2B events is the dependent variable, the level of uncertainty is a moderator, and the level of attention is a mediator.

Table 2: Hypotheses summary

	Hypotheses
H1A	For customers with a relatively low uncertainty level, persuasive types of advertisements have a stronger positive impact on customer intentions, compared to informative advertisements.
H1B	For customers with a relatively high uncertainty level, informative types of advertisements have a stronger positive impact on customer intentions, compared to persuasive advertisements.
H2	The effect of different types of advertising on customer intentions towards B2B events is mediated by customer attention.

Figure 2: Empirical model



5. Methodology

5.1. Advertisement effectiveness and self-reported bias

Having discussed in earlier sections, advertising can aim for different things, namely, to inform or persuade, and those goals can be achieved using different types of ads (informative or persuasive types). It raises the question though as to how an advertiser should measure whether their perceived goal is achieved, in other words whether the advertisement has been effective.

Advertisement effectiveness is defined as ¨the measurement of the results of an advertising campaign or particular advertisement, which must in turn be defined in terms of the achievement of the advertising objectives which the advertiser set for his campaign/advertisement¨ (Beerli & Santana, 1999). In literature, there are some measurements for effectiveness that are often used, for example:

1. Purchase intention: an indication to what extent people are willing and inclined to purchase a product or service (Teichert et al., 2018). Purchase intention can be an indication for sales, but can be very different from actual sales, as people not always do what they say (in literature referred to as stated instead of actual behavior). We can say that purchase intention is a self-reported measure for advertisement effectiveness. Purchase intention can be measured in multiple ways, for example using a Likert Scale (Lee & Shin, 2010).
2. Customer attitude: this measurement can be used when people are already familiar with products, to test whether an ad caused an attitude shift, or to measure what attitude the ad has generated when subjects are unfamiliar with a product. Customer attitude can be measured in multiple ways, for example by measuring the attitude towards the brand or product or through persuasion[3] and liking tests[4] (Beerli & Santana, 1999).
3. Awareness: is the customer aware of the product or brand? Awareness can also be defined as "ad recall" (Zhang & Yuan, 2018), and is common measure of effectiveness in the early stages of either a product life cycle or decision making process. Awareness can be measured in various ways, for example with a customer survey or questionnaire.

To summarize, there are multiple ways to determine whether an ad is effective, and in this study. In this study, I use *Intention* as a measure for advertisement effectiveness, similar to purchase intention, however in the case of events it can be seen as "attending intention". I measure the intention by asking respondents how likely they would be to attend an event, which means *Intention* is a self-reported

[3] Persuasion tests test whether the advertisement is able/strong enough to achieve an attitude change (Beerli & Santana, 1999)
[4] Liking tests test whether the advertisement is pleasing for a customer to look at, as pleasing ads often create a more positive customer attitude (Beerli & Santana, 1999)

measure. Self-reported measures are based on data that relies on an individual's own report of their attitude, beliefs or behavior.

However, self-reported measures do come with some issues that need to be addressed (Rindfleisch et al., 2008):

1. It suffers from self-reported bias (i.e., the stated preference bias) which pollutes the results.
2. Often self-reports are correlational in nature, and it is therefore very hard to establish causal evidence (i.e., to prove a causal relationship)

These problems make it difficult to assess whether advertisements actually have the desired effect. Fortunately, both can and are solved in this paper in the following way:

1. To overcome self-reported bias, a researcher can use measures that are not self-reported. In this paper, I use eye-tracking technology to test for attention, which is a non-self-reported measure, and therefore helps to overcome self-reported bias. In section 5.2, the concept is explained in more detail.
2. To make causal inferences, an experiment is required. In this paper, I conduct a laboratory experiment to be able to make causal inferences. In section 5.3, the experimental design will be discussed in more detail.

5.2. Eye Tracking

5.2.1 Eye tracking as a measure to overcome self-report bias

Academic research often encounters the issue of self-reported bias, where a disparity can arise between stated thoughts or actions and actual thoughts or actions. In advertising, it is important to acknowledge the existence of these differences, as stated preferences do not always correctly predict actual behavior (Quaife et al., 2018). To mitigate the impact self-reported bias, a researcher can use measures that do not rely on self-reported data.

Eye tracking is one of those measures. In marketing and especially in advertising, eye tracking is often used to serve as a measure for attention, and differences are found. BookingSweden, a Swedish startup that tries to compete with larger companies like Booking.com by offering more local experiences for a fairer price, conducted such a study (Tobii, n.d.). Prior to their launch, the company wanted to test how customers navigated their website, and with eye tracking they found that one of their main features on the website did not catch the customer's attention as they said it did. Based on the result of this study, the company made multiple changes with both these and other features and has now launched their website.

A study conducted by Scott, Green and Fairley (2016) found something similar. They evaluated the difference between self-reported advertisement effectiveness and revealed advertisement effectiveness in tourism advertising. The study used eye-tracking to determine people's attention while looking at an ad and used questionnaires to get an idea of their (self-reported) intentions towards the advertisement. In this study, significant differences were found between the two.

5.2.2 Eye tracking as measure for attention in mediating studies

As explained in the hypothesis development, I expect that attention plays a mediating role in the relationship between advertisement posters and customer intentions. In many of the studies hypothesis 2 is based on, eye tracking was used as well to measure attention (Boscolo et al., 2021; Pieters & Wedel, 2004; Maughan et al., 2007; Lee & Ahn, 2014).

For example, when Maughan et al. (2007) and Lee & Ahn (2014) found a positive correlation between attention and evaluation or attitude of the advertisement, they defined attention by the number of fixations and the duration of fixations. In the study by Scott, Green and Fairley (2016), which also showed the difference between self-reported data and eye tracking data, attention was reflected by the fixation frequency and duration, which are both positively correlated with attention.

Finally, a study conducted by Zhang & Yuan (2018) tested the relationship between attention and consumer's attitude. They defined attention as a function of TFT (transformed fixation time, i.e., the ratio between fixation time on the AOIs and the AOIs display time) and found a positive relationship with consumer's attitude towards the ad.

The literature discussed above proves the following two things. First, it is important to include both self-reported as well as revealed data when testing for advertisement effectiveness, as the two can differ significantly (Scott et al., 2016). Secondly, eye tracking is a common measure for attention and can be used to assess the relationship between advertisement posters and customer intentions.

5.3. Experimental Design

I conducted a laboratory experiment to test my predictions about the relationship between advertisement posters and customer intentions, where 1) it is expected that customers with low uncertainty level have a more positive intention when influenced by persuasive advertisement, 2) customers with a high uncertainty are expected to have a more positive intention when influenced by informative advertisement, and 3) that the effect of different types of advertisement posters is mediated by attention, which was measured with eye tracking technology.

This research has a focus on the B2B event industry, and therefore I tested various types of posters (informative and persuasive) for multiple B2B events. A graphical representation of the experimental flow can be found in Appendix B.1, Figure 8.

5.3.1 Participants and Experiment Manipulations

This laboratory experiment was conducted at the Erasmus Behavioral Lab. Of the 60 subjects that participated (> 50% between 18 – 23, 60% female), most of them are students at the Erasmus University. The dependent variable of this research is *Intention*, i.e., how likely the subject would be to attend the event, which I retrieved with a questionnaire. I test the effect of different types of posters, as well as different uncertainty levels. These two elements are both manipulated in the experiment, yielding four "treatment cells", represented in Table 3.

Table 3: Overview of the experimental treatment combinations

	Informative poster	Persuasive poster
Low uncertainty level	Cell 1	Cell 2
High uncertainty level	Cell 3	Cell 4

5.3.2 Procedure

Participants were informed about the study via text or in real life, and the subject pool consisted of friends, family, acquaintances and students who received bonus points for their participation in the experiment. Prior to the experiment, the only information the subjects received about the study was that it was an eye tracking study with posters for my Marketing Thesis research, but they did not receive any information about the purpose, nor about what manipulations were performed.

Upon entering the Behavioral Lab, the participants were seated in front of the Tobii Eye Tracker[5], which is a small black rectangle below the computer screen. Details about the eye tracking setup can be found in Appendix B.2. The experiment was designed in a program called E-prime[6], in which all questions, as well as the stimuli, were included. To gather the eye tracking data within the experiment, the Tobii Eye Tracker was linked to E-prime.

The experiment started with an introduction and subjects were asked to answer some general multiple-choice questions (gender, age, education, job experience and familiarity with B2B events). Details and the complete written out questions can be found in Appendix B.3. After the introduction and general questions, the eye tracker performed a calibration (Appendix B.2, Figures 11 and 12), to be able to correctly track the eye movements while looking at the posters. The subject had to follow a

[5] For more information about the Tobii Eye Tracker: https://www.tobii.com/products/eye-trackers
[6] For more information about E-prime: https://pstnet.com/products/e-prime/

dot to five different focus points, and when the calibration was successful, the researcher (me) accepted the calibration.

Once the eye tracker was correctly calibrated, the actual experiment started. This research has four different treatment cells, as stated previously, and in order to guarantee a complete within subject design, the trial that is explained below repeated itself four times per subject, for four different B2B events. Per trial, the "treatment cell" was different, and a poster for a different event was shown each trial.

The posters for the B2B events featured four different events: a conference about the public space, a product launch of an explosion proof phone, a bike industry festival and a Microsoft iCloud security workshop. The brands that are featured are real, however the events are hypothetical. The reason I chose these specific events is twofold. One, it was important to select events that were different from each other, to ensure variation in settings in order to avoid bias due to a single setting setup. Two, I chose events that most people, and especially students, are not that familiar with and would not necessarily think of attending. Otherwise, subjects could be biased in advance because they would attend the event in real life anyway, and the manipulations might not have the desired effect.

Each trial started with an introductory text about the event, either with much information (i.e., a low uncertainty level) or little information (i.e., a high uncertainty level). The low and high uncertainty level introductory texts only differed in the lines where the manipulation took place. For the high uncertainty level, doubt or uncertainty was created, for example by saying that the subject has never attended the event before or that the event is new. For the low uncertainty level, a subject was told that for example he/she already attended the event in the past two years, or that colleagues already told them about the event. In Appendix B.4, the introductory texts per event can be found (eight in total, four events x two versions of the text).

After the introductory text, and a brief recalibration for the eye tracker to relocate subject's pupils, an advertisement poster was shown, either an informative one or a persuasive one.

Each poster is compiled by a picture including the company logo on the left, and a text with a plain background on the right, in line with the key elements determined in the literature review. The posters were designed on Canva[7], where the ratio picture/text is 50/50 and the posters were saved with 1600 x 1000 pixels resolution. The brands, including the logo, are all real, but the posters are created

[7] Canva is a free online design tool, that can be used to create presentations, social media posts or, in this case, advertisement posters (https://www.canva.com/)

especially for this experiment, and kept relatively simple. When designing and creating the posters, I defined two Areas of Interest for each poster. An *Area of Interest* (AOI) is a "specifically defined region in the stimulus that the researcher is interested in gathering data about" (Holmqvist & Andersson, 2017, page 187). After defining an AOI, it is possible to extract eye tracking metrics specifically for those regions. For example, you can calculate how long and how often a subject looks at a specific region. In this experiment and for all posters, I defined two Areas of Interest: 1) the picture on the left and 2) the text on the right.

For each event, between the informative and persuasive posters, the differences were minor. The visual element, i.e., the picture with the logo, was kept the same between the two. This is for two seasons; one, a picture has a lot of different elements and factors that can influence the fixation time. Therefore, it would be very difficult to determine whether the fixation time between the informative and persuasive poster differs because the poster is informative or persuasive, or because of all the other factors that play a role (colors, number of people on the picture etc.). And two, finding a picture that is purely informative and purely persuasive is very difficult, if not impossible.

The textual element on the poster is where the manipulation happens. For every informative poster, the text is purely informational, solely practical information about the event, and nowhere does the poster try to persuade the subject to attend the event. To the contrary, the persuasive posters have no information at all and only include emotional elements and highly charged adjectives to persuade the subject to attend the event. In Appendix B.5, all the posters can be found (eight in total, four events x two types of posters).

While the poster was on the computer screen, the Tobii Eye Tracker tracked subject's pupils at a rate of 250 Hz, which is the refresh rate, also called the sampling rate. A *refresh rate* of 250 Hertz (Hz) means that per second, the screen and therefore the poster is refreshed 250 times. This means that we measure a new "fixation" every four milliseconds (1 second = 1000 milliseconds / 250 = 4 milliseconds). Every eye tracking session produces a huge dataset with raw data, with metrics like gaze positions for both pupils, the AOI the gaze was on at a specific moment and the duration of a certain fixation. This raw data is processed through an E-prime Analyzing program and provides data that can be cleaned and prepared for analyzing. The final measures that are used in the analyses are discussed in detail in section 5.4. The subjects could decide when they were finished looking at the advertisement poster by clicking their mouse. At that moment, the eye tracking for that specific trial stopped.

At the end of the trial, in order to uncover a subject's intentions towards the event, I asked the subject how likely they would be to attend the event on a 5-point Likert Scale. They also answered the questions “How much did the poster capture your attention?” (also on a 5-point scale) and “What element captured the most attention?” (Picture or text).

Because I want to ensure that the manipulations are successful, I also included a manipulation check at the end of each trial. The subjects had to indicate on a 5-point scale, from completely disagree to completely agree, how uncertain they felt when deciding whether to attend the event (before seeing the poster), and how much information they think the ad provided (again, for the complete overview of all the questions, see Appendix B.3).

5.3.3 Details about the randomization of the experiment

To be able to make causal inferences, the experiment needs randomization. In the experiment, the subjects are randomly exposed to four different posters, showing four different events. Subject never saw both the informative and persuasive poster of the same event, every poster was for a different event.

The experiment follows a complete within subject design. That means that all subjects were randomly assigned to each ¨treatment cell¨ once. In other words, every subject once saw an informative poster when the uncertainty level was high, once an informative poster with low uncertainty level, once a persuasive poster with low uncertainty level and once a persuasive poster with a high uncertainty level.

Because the technology of the eye tracking had some small limitations, it was not feasible for me to fully randomize the mix between event and treatment. Instead, I generated two versions of the experiment. One version showed informative posters for the Conference and Workshop and persuasive posters for the Product Launch and Festival, while the second version was the other way around. This design ensures that treatment and events are counterbalanced, avoiding bias, without the need for full randomization. In other words, when a subject got to see an informative poster about the conference, he or she automatically also saw an informative poster about the workshop and persuasive posters for the product launch and festival, and vice versa. Thus, which of the two versions a subject was assigned to was random.

To summarize, the order in which the events were presented, as well as which treatment cell the subject was assigned to, and the order of the type of poster and uncertainty level were all random. However, every subject was assigned to each treatment cell once, which is not random.

5.4. Measures

5.4.1 Variable overview

To answer my research question, and to test the hypotheses, I performed statistical tests in STATA, using the data retrieved from the experiment. Table 4 shows an overview of all variables retrieved from the Excel data files, followed by a more detailed explanation. In Appendix B.6, Table 18, a Table is included with all variables that are generated during process of analyzing.

Table 4: Summary of the variables

Name of Variable	Type of Variable	Clarification
Gender	Binary variable	1 = male and 2 = female
Age	Categorical variable	1 = under 18, 2 = 18 – 23, 3 = 24 – 29, 4 = 30 – 35, 5 = over 35
Education	Categorical variable	1 = Primary School, 2 = High School, 3 = Bachelor, 4 = Master's, 5 = PhD
JobExperience	Categorical variable	1 = less than 1, 2 = 1 – 5, 3 = 6 – 10, 4 = 11 – 15, 5 = 16 – 20, 6 = more than 20
Familiarity	Ordinal variable	Indicating how familiar a subject is with B2B events, ranging from 1 (not at all) to 5 (very familiar)
PersuasivePoster	Binary variable	0 = informative poster and 1 = persuasive poster
UncertaintyLow	Binary variable	0 = high uncertainty level and 1 = low uncertainty level
Event	Categorical variable	1 = conference, 2 = product launch, 3 = workshop and 4 = festival
Intention	Ordinal variable	Indicating how likely a subject would be to attend the event, ranging from 1 (not at all) to 5 (very likely)
ManipulationUncertainty	Ordinal variable	Indicating how uncertain a respondent felt, ranging from 1 = not uncertain to 5 = very uncertain
ManipulationPoster	Ordinal variable	Indicating how much information a subject felt the poster provided, ranging from 1 = no information at all to 5 = a lot of information
AttentionStated	Ordinal variable	Indicating how much the poster captured a respondent's attention according to the respondent, ranging from 1 (not at all) to 5 (a lot)
AttentionStated4	Ordinal variable	Like AttentionStated, however now ranging from 0 to 4 instead of 1 to 5

AttentionStatedElement	Binary variable	Indicating what element captured the most attention according to the respondent, 0 = picture and 1 = text
ViewingTime	Continuous variable	Variable that indicates the number of milliseconds the poster was on the screen within a trial
NOFTotal	Continuous variable	Variable that counts the number of fixations per trial for on the poster
NOFText	Continuous variable	Variable that counts the number of fixations on the textual AOI within a trial
NOFPicture	Continuous variable	Variable that counts the number of fixations on the visual AOI within a trial
GDTtotal	Continuous variable	Variable that counts how long all fixations on the poster lasted together within a trial
GDText	Continuous variable	Variable that counts how long all fixations on the textual AOI lasted together within a trial
GDPicture	Continuous variable	Variable that counts how long all fixations on the visual AOI lasted together within a trial
AFDTotal	Continuous variable	Variable that indicates how long a single fixation lasted on average, within the trial on the poster
AFDText	Continuous variable	Variable that indicates how long an average fixation lasted on the textual AOI within a trial
AFDPicture	Continuous variable	Variable that indicates how long an average fixation lasted on the visual AOI within a trial

5.4.2. Intention

Intention is the dependent variable in all analyses. In hypotheses 1A and 1B, I stated that customer's, depending on their uncertainty level, have a more positive intention towards an event when influenced by a certain type of advertisement poster. Because I want to test subject's intention towards an event, the variable *Intention* is based on how likely a subject is to attend the event after looking at the advertisement poster (question 1, Appendix B.3).

5.4.3. Attention

5.4.3.1. Viewing time

The viewing time is the time the poster was shown on the screen, before the subject decided to click through to the questions. This is not necessarily the time respondents actually looked at the poster and processed it, as the viewing time also includes moment/fixations that are not on the poster. This could be because the respondent closed the eyes, looked somewhere other than the screen or the eye tracker was simply not able to track the eye. All these moments are included in the viewing time. Still, this is a good indication of attention, as when the poster is on the screen, a subject is either looking at it or it is on one's mind. Therefore, I still assume that the longer the viewing time, the more attention the subject has.

5.4.3.2. Number of Fixations (Total, Text, Picture)

These variables count the number of individual fixations that are either on the entire poster (*NOFTotal*) or on one of the AOI's (*NOFText* or *NOFPicture*). Note that for these variables, all fixations that do not meet the requirements are dropped from the data set. The detailed explanation of what a fixation is (for example minimum fixation duration) and when they are dropped from the data set can be found in Appendix B.7. As there are only two AOI's on each poster (the picture and text), this logically means that the *NOFTotal* is the sum of *NOFText* and *NOFPicture* for each observation.

5.4.3.3 Gaze Duration (Total, Text, Picture)

These variables are the sum of all individual fixations on either a certain AOI (*GDText* and *GDPicture*) or these two together, on the entire poster (*GDTotal*). So, where the previous variables are the number of fixations summed up, these are the durations of those fixations summed up, in milliseconds. Note that these Gaze Durations only include the actual fixations, not the ones that are dropped from the data set (Appendix B.7). Therefore, *GDTotal* will always be either the same or smaller than *ViewingTime* for each observation.

5.4.3.4 Average Fixation Duration (Total, Text, Picture)

These variables indicate how long a single fixation on average lasted, either on the textual element (*AFDText*), the visual element (*AFDPicture*) or the average of those two, on the entire poster (*AFDTotal*).

5.4.3.5. Computing an "Attention Index Score"

I use subject's viewing time and eye movements (i.e., fixations and gazes) as an objective measure for attention by creating a "Attention Index Score". The use of such composite indexes is common both in attention research (Steinman et al., 1997; Briggs et al., 2013), as well as in more general in engagement research (Chatterij et al., 2016). The Attention Index Score is computed by taking the sum of the standardized values of the following four variables:

- *Viewing time* (X_1): the viewing time represents the period that the stimulus (i.e., the advertisement poster) was shown. This in an indication of "overall efficiency and effort needed to complete the task" (Van der Lans & Wedel, 2017).
- *Total number of Fixations* (X_2): this variable is one of the most used metrics in visual attention and eye tracking marketing research, both on the entire stimuli and on specific

AOI's (Wedel & Pieters, 2017; Aribarg et al., 2010). The total number of fixations is highly correlated with viewing time and is therefore also an indication of efficiency and effort (Van der Lans & Wedel, 2017). According to Aribarg et al. (2010), fixation frequency is a common indication of ad recognition and ad recall.

- *Total Gaze Duration* (X_3): according to Van der Lans & Wedel (2017), gaze duration, either on a stimulus or on a specific AOI, is highly correlated with the total number of fixations and is also a good measure for ad recognition and ad recall.
- *Total Average Fixation Duration* (X_4): according to Holmqvist et al. (2011), the *AFD* for a specific AOI is a good indication of depth of processing, as the more complicated the stimuli is, the longer the fixations will last. This also holds for the *AFD* for the entire stimuli, as this can also be used to reflect task difficulty (Vlaskamp & Hooge, 2006). Therefore, the *AFD* for the entire poster will also be included in the Attention Index Score.

By creating an attention index score with these four variables, I am able to consider all expressions of attention (recognition, recall, depth of processing, task difficulty and overall effort). However, each of these variables have very different scaling properties, which is the reason I need to standardize them before summing them up. For example, the viewing time is presented in milliseconds, and be up to 40.000 (milliseconds), whereas the number of fixations in an absolute number and has a maximum of 22 (fixations). In order to standardize these four variables, I deduct the mean from every case, and divide this by the standard deviation of this variable:

$$z_i = \frac{X_{ki} - \mu_{ki}}{\sigma_{ki}}$$

In the Equation above, k = 1 to 4, indicating the four variables described above. In STATA, I generated four standardized variables for *ViewingTime*, *NOFTotal*, *GDTotal and AFDTotal (*Appendix B.6, Table 18). I summed the four standardized variables to create the *AttentionIndex:*

$$AttentionIndex_i = z1ViewingTime_i + z2NOFTotal_i + z3GDTotal_i + z4AFDTotal_i$$

Note that given standardization, each of the four variables is normally distributed with a zero mean (i.e., $\mu_k = 0$), and a variance of 1 (i.e., ${\sigma^2}_k = 1$), which allows me to define the distribution of my Attention Index as follows:

$$AttentionIndex_i \sim N\left(\sum_{k=1}^{4} \mu_k , \sum_{k=1}^{4} \sigma_k^2\right)$$

Or, more simply:

$$AttentionIndex_i \sim N(0,4)$$

In practice, this means that my *AttentionIndex* is centered at zero with a standard deviation of 2, which means that most observations (95%) will lie in the interval between -3,92 and 3,92 (2*1,96), where the values below -4 indicate “lowest attention”, value around 0 indicates “average attention” and values above +4 indicate “highest attention”.

6. Results

6.1. Descriptive Statistics

6.1.1 General Information

In total, 60 subjects participated in the laboratory experiment. With each subject participating in four trials, this provided me 240 observations, 60 per "treatment cell", as the experiment had a complete within subject design. However, despite the calibration of the eye tracking, some eye tracking data is not usable for analysis, leading to the drop of 17 observations. An explanation of why these observations were dropped from the sample can be found in Appendix C.1.2.1. However, the eye tracking data is only used for hypothesis 2, where I test whether attention has a mediating role on the relationship between the type of poster and the customer intentions. Therefore, for the analysis of hypotheses 1A and 1B, the manipulation checks as well as the descriptives below, all 240 observations are used. For the mediating part (hypothesis 2), the 17 failed observations are dropped from the sample.

Table 5 contains descriptive statistics about the 60 subjects, like age, job experience and gender. In the sample, 40% of the respondents are male and 60% are female, and most subjects are between 18 and 23 years old. The majority of the subjects, just over 50%, completed a Bachelor and this is logically followed by the fact that more than 75% of the subjects had under 5 years of job experience. More detailed information and graphical representation of the data can be found in Appendix C.1.1, Figure 22.

Table 5: Descriptive statistics 60 subjects

N = 60	Categories	Number	Percentage
Education	1 – Primary School	0	0%
	2 – High School	18	30%
	3 – Bachelor	32	53,33%
	4 – Master	10	16,67%
	5 – PhD	0	0%
Age	1 – Under 18	0	0%
	2 – Between 18 and 23	36	60%
	3 – Between 24 and 29	21	35%
	4 – Between 30 and 35	0	0%
	5 – Over 35	3	5%
Gender	Male	24	40%
	Female	36	60%
JobExperience	1 – Less than 1 year	19	31,67%
	2 – Between 1 and 5 years	28	46,67%
	3 – Between 6 and 10 years	10	16,67%
	4 – Between 11 and 15 years	0	0%
	5 – Between 16 and 20 years	0	0%
	6 – More than 20 years	3	5%
Familiarity with B2B events	1	20	33,33%
	2	13	21,67%
	3	16	26,67%
	4	7	11,67%
	5	4	6,67%

6.1.2 Eye Tracking Descriptives

For the eye tracking analysis, the data set consists of 223 observations (again, why the other observations were dropped is explained in Appendix C.1.2.1). In Table 7, descriptive statistics can be found. Because some observations were dropped due to "failed" eye tracking or outliers, there is no longer a complete within subject design for the analysis of hypothesis 2. Therefore, not every treatment cell includes 60 observations anymore. The distribution is the following (Table 6):

Table 6: Distribution observations over treatment cells

	High uncertainty level	Low uncertainty level	Total
Informative poster	55	58	113
Persuasive poster	60	50	110
Total	115	108	223

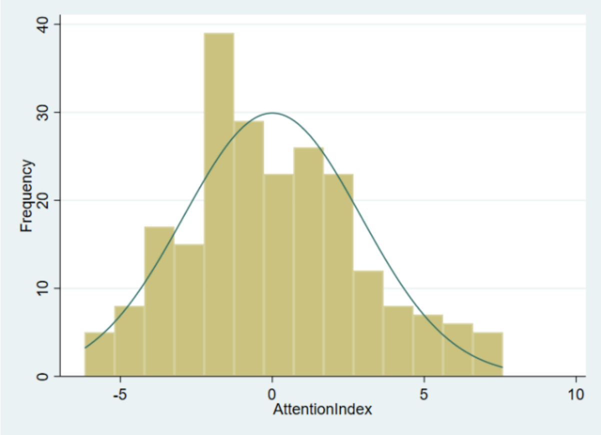
The average viewing time, i.e., how long the poster was on the screen for, is 12134,88 milliseconds (about 12 seconds), before the respondents clicked through to the questions. During this period, the subjects looked at both the textual and visual element (i.e., text and picture AOI), with a bias towards the textual element, as the average *GDText* (i.e., the sum of all fixations on the textual element) was 6696,933 milliseconds and the *GDPicture* was 4990,278 milliseconds. This difference is significant at a 1% significance level (p= 0,000, Appendix C.1.2.2., Table 19).

Table 7: Descriptive Statistics Eye tracking Data

N = 223	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
ViewingTime	223	12134,88	11537	4226,349	4156	24154
NOFTotal	223	6,991	6	2,924	2	22
NOFText	223	3,641	3	1,726	1	12
NOFPicture	223	3,350	3	1,431	1	10
GDTotal	223	11683,93	11121	4147,037	969	23628
GDText	223	6696,933	6316	2743,211	960	16100
GDPicture	223	4990,278	4912	2282,558	428	12476
AFDTotal	223	1801,186	1708	683,420	242,25	4389,333
AFDText	223	2065,856	1897	978,220	480	7121
AFDPicture	223	1657,135	1364	961,058	251,2	7620

The distribution of the Attention Index Score can be found in Figure 3. As can be seen, the variable *AttentionIndex* follows a relatively normal distribution and there are no real outliers.

Figure 3: Distribution of Attention Index Score



In Table 8, descriptive statistics can be found. Because the variables are standardized, the standard deviation is per definition always 1 and the mean is or closely approaches 0, and therefore these statistics are excluded from the descriptives.

Table 8: Descriptives Standardized Variables & Attention Index Score

N = 223	Observations	Median	Minimum	Maximum
AttentionIndex	223	-0,288	-6,177	7,586
(z1ViewingTime)	223	-0,141	-1,888	2,844
(z2NOFTotal)	223	-0,339	-1,707	5,133
(z3GDTotal)	223	-0,125	-2,573	2,891
(z4AFDTotal)	223	-0,136	-2,281	3,787

6.2. Manipulation checks

Before I analyze the data, it is important to test whether the two manipulations in the experiment were successful. As a reminder, I manipulated the uncertainty level of the customer, as well as the level of information the posters provided about the event. To check whether the manipulations worked, I asked control questions at the end of each trial to examine how uncertain subjects felt, and if they felt the advertisement posters provided a lot of information (Appendix B.3). In section 6.2.1. and 6.2.2., I explain both manipulation checks in more detail, and conclude that the informative versus persuasive manipulation was successful at a 1% significance level, whereas the low versus high uncertainty manipulation was close to significance ($p = 0.149$) but is not significant at a 10% significant level.

6.2.1. Manipulation level of information

Table 9 contains the main results of the manipulation check test for the manipulation of the level information. In Appendix C.2, Table 20, the details of this test can be found. The statement at the end of each trial was “I feel that the ad provides a lot of information about the event” and the subject could indicate on a 5-point scale how much they agreed, from 1 being completely disagree to 5 being completely agree. Thus, the higher the number, the more a subject thought the poster was informative.

Table 9: Output manipulation check level of information on poster

N = 240	Subject with informative poster	Subjects with persuasive poster	T-test p-value
Average answer Manipulation check (note, the higher, more information)	3,025	1,917	0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

The subjects with an informative poster answered 3,025 on average, whereas the subjects with a persuasive poster answered 1,917 on average. That means that the manipulation was successful, as the subjects with an informative poster on average felt that the poster provided more information than the people with a persuasive poster. This difference is significant at a 1% significance level, indicating that the manipulation regarding the information level was successful.

6.2.2. Manipulation level of uncertainty

In Table 10, the most important output of the manipulation check test can be found for the manipulation of the uncertainty level. In Appendix C.2, Table 21, the details of this test can be found. The statement at the end of each trial was “Before I saw the poster, I felt uncertain about attending the event” and the subject could indicate on a 5-point scale how much they agreed, again 1 being completely disagree and 5 completely agree. Thus, the higher the number, the more uncertain a subject felt.

Table 10: Output manipulation check uncertainty level

N = 240	Subject with high uncertainty level	Subjects with low uncertainty level	T-test p-value
Average answer Manipulation check (note, the higher, the more uncertain)	2,942	2,8	0,149

The subjects that were manipulated to be more uncertain, i.e., that received less information prior to the advertisement poster, had an average answer of 2,942, where the subjects with a low uncertainty level answered 2,8 points on average, a much smaller difference compared to the information manipulation.

Even though the manipulation check did not reach the desirable significance level (p = 0,149 > 0,05), the sign is still in the expected direction, indicating that the manipulation did work to some extent. There can be multiple reasons the manipulation did not have a significant effect, one of them being that the manipulation simply was not strong or exaggerated enough. However, given the limited sample size and the fact that the p-value does approach the desired significance level ($p < 0.15$), I think is satisfactory and allows me to continue with analyzing the data.

6.3. Control Variables

I also include some control variables in the regression, since some variables can influence the dependent variable intentions. Potential control variables are age, gender, education, familiarity with B2B events, job experience and type of event the poster was for. One would expect correlations between the dependent variable and control variables, but because of the small sample size, not all correlations are significant. Still, it is better to include some control variables to control for individual characteristics. In Appendix C.3., the results of the correlation tests can be found (Table 22).

6.3.1. Age ang Education, Job Experience and Familiarity with B2B events

Age, education, familiarity and job experience could all be correlated with the intention towards B2B events. However, it is not possible to include all as control variables in the regression, as some might be correlated with each other, which would create multicollinearity and that is a problem.

As I expected, *Familiarity* and *JobExperience* are correlated (0.356) but both do not have a strong correlation with *Intention* (0,009 and -0,009, respectively). Both *Familiarity* and *JobExperience* are correlated with *Age* (0,527 and 0,506, respectively), and *Age* does have a correlation with *Intention* (0,17). This means that out of the three, only one should be included in the regression, and as *Age* has a much stronger correlation with *Intention*, I choose to exclude both *Familiarity* and *JobExperience*.

Secondly, there could also be a relationship between *Age* and *Education*, as subjects that are younger are probably still studying, so therefore older people will probably have a higher level of finished education. This is confirmed when I look at the correlation, which is 0,467. The correlation between *Education* and *Intention* is only 0,053, and therefore *Education* is also excluded from the regression.

Conclusively, as these four variables cause multicollinearity is they are all included, and because *Age* has the highest correlation with *Intention*, I only include *Age* as a control variable of these four.

6.3.2. Event type

I also tested whether the type of event that was presented was correlated with the intention subjects had towards the event. To do this, I performed a Cramer V test, which can be used to test correlation when dealing with a categorical variable[8]. Even though the Cramer V value is not extremely high (0.1657)[9], there is a positive bias towards event 3 (workshop) and a negative bias towards event 2 (product launch). Therefore, I include the type of event in the regression. As the type of event is a nominal categorical variable, I created four dummy variables, *EventConference*, *EventProductLaunch*, *EventWorkshop* and *EventFestival.* To avoid a dummy variable trap, I exclude one as a reference event and include the rest in the analyses as separate variables.

Table 11: Cramer V test to test correlation between Event type and Intention

	Intention					
Event number	1	2	3	4	5	Total
1 (Conference)	8	16	18	17	1	60
2 (Product launch)	10	19	19	9	3	60
3 (Workshop)	2	13	18	26	1	60
4 (Festival)	3	20	19	16	2	60
Total	23	68	74	68	7	240

Cramer's V = 0,1657

6.3.3. Gender

I would not directly expect a correlation between gender and intention towards B2B events, as this also did not come forward in the literature review. I tested for it anyway, and as expected, there is only a small correlation between *Gender* and *Intention* (- 0,015, Appendix C.3., Table 22). Therefore, I do not include *Gender* in the regression as a control variable.

6.4. Hypotheses 1A and 1B

As a reminder, for hypotheses 1A and 1B, I want to test the relationship between the type of advertisement poster and customer intention, considering the moderating role of the uncertainty level of the customer on this relationship. I expect a positive interaction between the variables *PersuasivePoster* and *UncertaintyLow*. Specifically, I expect that for customers with a relatively low uncertainty level, persuasive advertisement posters have a stronger positive impact on *Intention* than informative advertisement posters (as stated in hypothesis 1A), whereas customers with a relatively high uncertainty level are assumed to be more positively influenced by informative posters compared

[8] https://www.statology.org/correlation-between-categorical-variables/. The Cramer V works best with 2 nominal categorical variables, which *Intention* is not, but the Cramer V value can still be interpreted with a continuous variable.
[9] The Cramer V can range between 0 and 1, 0 meaning that there is no correlation between the variables at all and 1 meaning that there is perfect correlation between the two variables. Rule of thumb is that under 0,1, the correlation is weak, and from 0,5, the correlation is strong. 0,3 indicates an average correlation.

to persuasive posters (as stated in hypothesis 1B). Note that because the eye tracking data is not used, all 240 observations are used in this analysis.

6.4.1 Procedure

To test for the moderating role of uncertainty, I created an interaction term between the type of poster and the uncertainty level, *PersuasivePoster*UncertaintyLow*. Remember that when *PersuasivePoster* is 1, the subject sees a persuasive poster, and 0 for an informative poster. For *UncertaintyLow*, the variable is 1 when the uncertainty level is low, and 0 if the uncertainty level is high. Therefore, the interaction term only has a value of 1 for subjects with a low uncertainty level who looked at a persuasive poster.

Following up on the information above, the following regression is formulated to test hypotheses 1A and 1B[10]:

$$\begin{aligned} Intention_i = \ & \beta_0 + \beta_1 PersuasivePoster_i + \beta_2 PersuasivePoster_i * UncertaintyLow_i \\ & + \beta_3 UncertaintyLow_i + \beta_4 Age_i + \beta_6 EventConference_i + \beta_7 EventProductLaunch_i \\ & + \beta_8 EventWorkshop_i + \varepsilon_i \end{aligned}$$

6.4.2. Results

I performed the linear regression in STATA, and the results can be found Table 12 below. I also ran a mixed model with a random intercept, in order to control for the fact that the observations are not independent from each other (every subject represents four observations that will probably be correlated). However, the statistical power or the coefficients were lower, and therefore I chose to use the output of the linear regression below. The results of the Random Intercept model are included though in the Appendix and can be found in Appendix C.4, Table 24. The R-squared of this linear regression model is quite low still (0,088), indicating that there are many other reasons why people would or wouldn’t intend to attend an event. Still, the type of advertisement has an effect as can be seen below.

[10] Note that the variable *EventFestival* is excluded from the regression to serve as a reference

Table 12: Regression output Hypotheses 1A and 1B

Intention	Coefficient	Standard Error	T	P-value	95% Confidence Interval	
PersuasivePoster	-0,302	0,182	-1,66	0,099*	-0,662	0,057
PersuasivePoster*UncertaintyLow	0,324	0,272	1,19	0,234	-0,211	0,860
UncertaintyLow	-0,014	0,171	-0,08	0,933	-0,352	0,323
Age	0,259	0,097	2,68	0,008***	0,069	0,450
EventConference	-0,116	0,183	-0,63	0,526	-0,477	0,245
EventProductLaunch	-0,279	0,189	-1,47	0,142	-0,651	0,094
EventWorkshop	0,284	0,175	1,63	0,105	-0,060	0,628
Constant	2,328	0,287	8,13	0,000***	1,764	2,893

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Number of Observations	240
F statistic (4, 235)	3,09
Prob > F	0,004
R-squared	0,088
Root MSE	0,995

6.4.3. Interpretation

6.4.3.1. Main effects of Type of Poster and Uncertainty Level

The coefficient of *PersuasivePoster* is -0,302, which is significant at a 10% significance level (p = 0,099). This means that independently of the uncertainty level, and keeping all other variables constant (i.e., ceteris paribus), on average, a persuasive poster decreases a subject's *Intention* towards the event with 0,3 points on the 5-point Likert Scale, compared to the same subject that saw an informative poster.

The coefficient *UncertaintyLow* is -0,014, which is very small and has a p-value of 0,933. This means that the level of uncertainty, regardless of the type of poster, has a neglectable effect on the *Intention* towards the B2B event, ceteris paribus.[11]

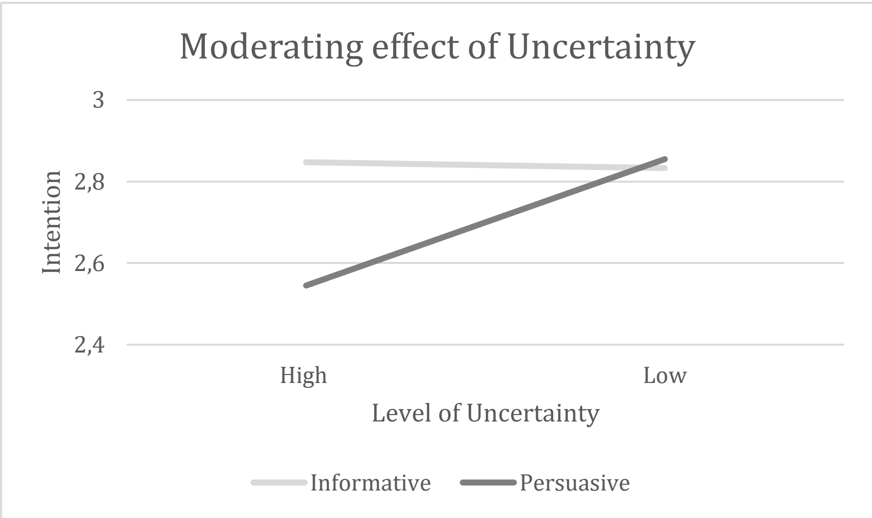
[11] This is probably an artifact of the manipulation of the uncertainty level, as this was not as strong or successful as the manipulation of the level of information in the poster.

6.4.3.2. Moderating Effect

To find support for hypotheses 1A and 1B, I look at the moderating variable, which is the interaction term between *UncertaintyLow* and *PersuasivePoster (PersuasivePoster*UncertaintyLow).* The p-value of the interaction term is not significant (p = 0,234 > 0,1), which leads to me reject hypotheses 1A and 1B. Note that this may be driven by my sample size and low statistical power to detect interaction effects.

In fact, visual inspection of the results suggests that the effects in the data are consistent with the moderation hypotheses (even though not statistically significant in my sample). For example, Figure 4 graphically represents the interaction between *PersuasivePoster* and *UncertaintyLow* on *Intention.*

Figure 4: Interaction between Uncertainty Level and Type of Poster on Intentions



Looking at the graph, it is clear that the two variables interact in the predicted direction, but the effect does not reach statistical significance. In other words, for with a high uncertainty level, the average *Intention* is higher for the informative poster compared to the persuasive poster. For subjects with a low uncertainty level, the average *Intention* is slightly larger with the persuasive poster compared to the informative poster but is hard to distinguish from a statistical perspective.

This Figure visually represents the interaction term reported in the regression output above, which indicates the moderator coefficient is 0,324. For completeness (and despite the p > 0,10) the interaction term can be interpreted in the following way.

6.4.3.3. Hypothesis 1A

A subject between 18 and 23 (*Age = 2)* and a low uncertainty level, that sees a persuasive poster about a B2B festival, has an average *Intention* of 2,855 (2,328 – 0,302 + 0,324 - 0,014 + 0,260*2, without intermediate rounding), while for the same subject where the only difference is an informative poster instead of a persuasive poster, i.e., ceteris paribus, the average *Intention* is 2,833 (2,328 - 0,014 + 0,260*2, without intermediate rounding). This means that on average, for subjects with a relatively low uncertainty level, a persuasive poster has a slightly stronger positive impact on their intention than informative posters. This can also be concluded by adding the coefficient for *PersuasivePoster* and the coefficient of the interaction term *PersuasivePoster*UncertaintyLow* (-0,302 + 0,324 = 0,022, similar to 2,855 – 2,833 = 0,022).

6.4.3.4. Hypothesis 1B

A subject between 18 and 23 (*Age = 2)* and a high uncertainty level, that sees an informative poster about a B2B festival, has an average *Intention* of 2,847 (2,328 + 0,260*2, without intermediate rounding), while for the same subject with a persuasive poster, ceteris paribus, the average *Intention* is 2,545 (2,328 – 0,302 + 0,260*2, without intermediate rounding). This means that on average, for subjects with a high uncertainty level, informative posters have a stronger positive impact on customers intentions than persuasive posters. This is also the effect I expected based on the literature.

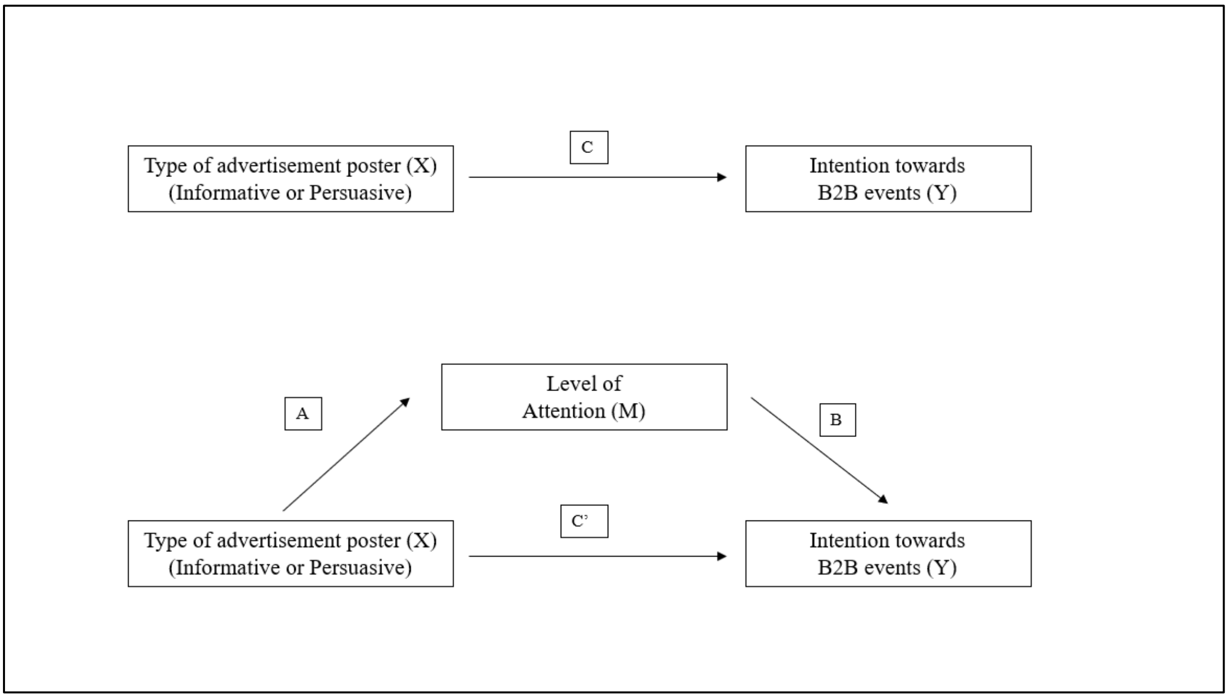
6.4.4. Conclusion

I reject 1A and 1B because the interaction term is insignificant (p = 0,234 > 0,10). Yet, I did find some indication that the relationship is as expected, and that especially for customers with a high uncertainty level, informative posters might be more successful than persuasive posters.

6.5. Hypothesis 2

As a reminder, hypothesis 2 states that the effect of different types of advertising on customer intentions towards B2B events is mediated by customer attention. This hypothesis is graphically represented in Figure 5.

Figure 5: Graphical representation of the mediating effect of Attention



Note that the data set that I use for hypothesis 2 consists of 223 observations, as I now use the eye tracking data and therefore dropped the "failed" observations and outliers.

6.5.1. Procedure

Originally, the most technique to test for mediation was based on Baron & Kenny's (1986), and followed the next steps:

1. First, I must prove the causal relationship the type of advertisement poster and the intentions towards B2B events (C, i.e., the total effect, see upper part of Figure 5 above), otherwise there is not even a relationship to be mediated.
2. Secondly, the type of advertisement poster needs to influence the Attention Index (prove A, lower part of Figure 5) and this in turn needs to influence Intentions (prove B, idem, Figure 5). In other words, the effect of advertisement poster on *Intentions* that runs through *AttentionIndex* (i.e., the indirect effect, AB) needs to be significant.
3. Conclusively, for a true mediation effect, the total effect and the direct effect need to differ to have an indirect effect (i.e., mediating effect) → The total effect (C) = Direct effect (C') + Indirect effect (AB) (Figure 5).

However, today, Baron & Kenny's (1986) approach to establish mediation is no longer accepted, as Zhao et al. (2010) criticized and rejected their procedure. In Zhao's evaluation, the Baron & Kenny model framework used unsuitable statistical tests to examine indirect effects, causing many studies to reject mediation where it might, in fact, exist. According to Zhao, it is possible to find mediation in many more cases, even if there is no path c (total effect). Zhao et al. (2010) argue that to establish mediation, the most important thing is to find a significant indirect effect (a x b) and suggests that the bootstrapping method used by Preacher & Hayes (2004) is suitable to do this. Therefore, I use this approach to find support or reject hypothesis 2.

6.5.2. Results

In order to test for the existence of an indirect (a x b) and therefore mediation effect, I ran the bootstrapped test of mediation proposed by Preacher & Hayes (2004), with 1000 bootstrapping samples/replications (Preacher & Hayes, 2008). The complete output of the analysis can be found in Appendix C.5 (Tables 25 – 27) and the most important results are summarized in Tables 13 and 14. In the mediation model, I controlled for *EventConference*, *EventProductLaunch*, *EventWorkshop*, *Age* and *UncertaintyLow*, like the analysis for hypotheses 1A and 1B[12]. I also included the interaction term between *PersuasivePoster*UncertaintyLow* as a control variable, because even though the moderating effect was not significant in the analyses of H1A and H1B, it gave an indication that the moderating role of uncertainty exists.

Table 13: Bootstrapping mediation output without percentiles

N = 223	Observed coefficient	Bootstrap Standard Error	Z – value	P – value	Normal based 95% Confidence Interval	
Indirect effect	0,002	0,018	0,13	0,896	-0,034	0,039
Direct effect	-0,277	0,188	-1,48	0,140	-0,645	0,091
Total effect	-0,275	0,186	-1,48	0,139	-0,639	0,090

[12] Note that again, *EventFestival* is excluded from the analysis to serve as a reference and to prevent a dummy variable trap

Table 14: Bootstrapping mediation output with percentiles

	Observed coefficient	Bias	Bootstrap Standard Error	95% Confidence Interval		
Indirect effect	0,002	0,0002	0,018	-0,034	0,045	P*
				-0,026	0,054	BC**
Direct effect	-0,277	-0,007	0,188	-0,641	0,097	P
				-0,638	0,109	BC
Total effect	-0,275	-0,007	0,186	-0,638	0,072	P
				-0,635	0,073	BC

*P = percentile

**BC = bias-corrected

6.5.3. Interpretation

6.5.3.1. Indirect Effect

The coefficient of the indirect effect is the key indicator of the mediation (Zhao et al., 2010). Without an indirect effect, there is no mediation. As can be seen in Tables 13 and 14, the coefficient of the indirect effect is 0,002, which is very small. The p-value of the coefficient is 0,896 a sign that even the very small indirect effect, is far from significant. In Appendix C.5, Table 25, it is clear that even though the “a coefficient” (path a, Figure 5) is almost significant, the reason the indirect effect is non-existent is due to the lack of a significant “b coefficient”. In other words, there is no relationship between the level of attention and customer intentions, and therefore there is no indirect effect.

This can also be seen by the confidence interval in Table 14. When the confidence interval does not include zero, the indirect effect can be considered significant. However, in Table 14, for both the percentile and bias-corrected intervals, zero is included which is another indication that the indirect effect is not significant.

6.5.3.2. Total and Direct Effect

Tables 13 and 14 provide information about the direct and total effect as well. The coefficient of the total effect is -0,275, and it’s associated p-value of 0,139 indicates that the result is approaching significance at a 10% significance level (as the p-value is smaller than 0,15). This means that there is an indication that the type of poster influences the customer intentions. This supports the conclusion drawn in hypotheses 1A and 1B, where I also found an indication that the type of poster affects customer intentions.

The direct effect is almost the same as the total effect (-0,277 and -0,275, respectively). This coefficient is also approaching a 10% significance level since the p-value is smaller than 0,15 (0,140). Because the two effects are almost the same, it means that there is little to no mediation, in other words, the effect of *PersuasivePoster* on *Intentions* is not mediated by *AttentionIndex*.

6.5.4. Conclusion

Conclusively, based on the approach by Zhao et al. (2010), there is no mediating effect of attention on the relationship between poster type and intentions, because the indirect effect is non-existent. In other words, I did not find support for hypothesis 2. In the discussion, some potential explanations are discussed why I did not find this mediating effect.

However, even though there is no mediating effect, it does not mean that the level of attention can't have any impact on the relationship between type of poster and customer intentions. In Chapter 7, the Post Hoc analysis, the moderating role of attention is explored.

7. Post-Hoc Analysis

7.1. Attention as a Moderator

In the analysis of hypothesis 2, I have used the *AttentionIndex* variable to discover whether this served as a mediator between the type of advertisement poster and customer intentions. There was no indirect effect and therefore I could not find grounds for a mediating effect of attention.

7.1.1. Expectations

However, the level of attention can still play a role in the relationship between the type of advertisement poster and the customer intentions. This is based on findings from previous literature, as discussed in the literature review.

While not hypothesized, the analyses I did suggests that a potentially interesting effect could be the moderating effect of attention levels on the relationship between the type of advertisement poster and the customer intentions. In other words, depending on the level of attention, one or the other poster could have a more positive effect on the customer intentions. For instance, a subject with a relatively low attention level could be more positively influenced by an informative advertisement poster, as an informative poster might be "easier to understand and process" and therefore requires less attention. On the other hand, a subject with a relatively high attention level, a persuasive poster might be better because when the attention is there, a persuasive poster might speak to a subject more, only it requires a certain level of attention.

7.1.2. Procedure

To test this effect, I created an interaction term between the *AttentionIndex* and *PersuasivePoster.* I ran a regression with *Intention* as dependent variable, *PersuasivePoster* as independent variable and included the interaction term *PersuasivePoster*AttentionIndex*, as well as *AttentionIndex*. I also included control variables, like the analysis for hypotheses 1A and 1B[13].

$$
\begin{aligned}
Intention_i = \ & \beta_0 + \beta_1 PersuasivePoster_i + \beta_2 AttentionIndex_i + \beta_3 PersuasivePoster_i \\
& * AttentionIndex_i + \beta_4 UncertaintyLow_i + \beta_5 PersuasivePoster_i \\
& * UncertaintyLow_i * + \beta_6 Age_i + \beta_7 EventConference_i + \beta_8 EventProductLaunch_i \\
& + \beta_9 EventWorkshop_i + \varepsilon_i
\end{aligned}
$$

[13] *EventFestival* is excluded from the regression

7.1.3. Results

In Table 15, the results of this regression can be found.

Table 15: Regression output Post-Hoc analysis

Intention	Coefficient	Standard Error	T	P-value	95% Confidence Interval	
PersuasivePoster	-0,270	0,190	-1,41	0,159	-0,644	0,106
AttentionIndex	-0,050	0,025	-2,01	0,046**	-0,100	-0,001
PersuasivePoster*AttentionIndex	0,106	0,040	2,64	0,009***	0,027	0,185
UncertaintyLow	0,009	0,183	0,05	0,963	-0,351	0,369
PersuasivePoster*UncertaintyLow	0,172	0,286	0,60	0,547	-0,391	0,735
Age	0,236	0,095	2,48	0,014**	0,049	0,424
EventConference	-0,183	0,194	-0,95	0,345	-0,565	0,199
EventProductLaunch	-0,268	0,199	-1,35	0,178	-0,660	0,123
EventWorkshop	0,270	0,179	1,51	0,133	-0,082	0,622
Constant	2,413	0,286	8,44	0,000***	1,850	2,977

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Number of Observations	223
F statistic (4, 235)	3,29
Prob > F	0,001
R-squared	0,111
Root MSE	0,978

7.1.4. Interpretation

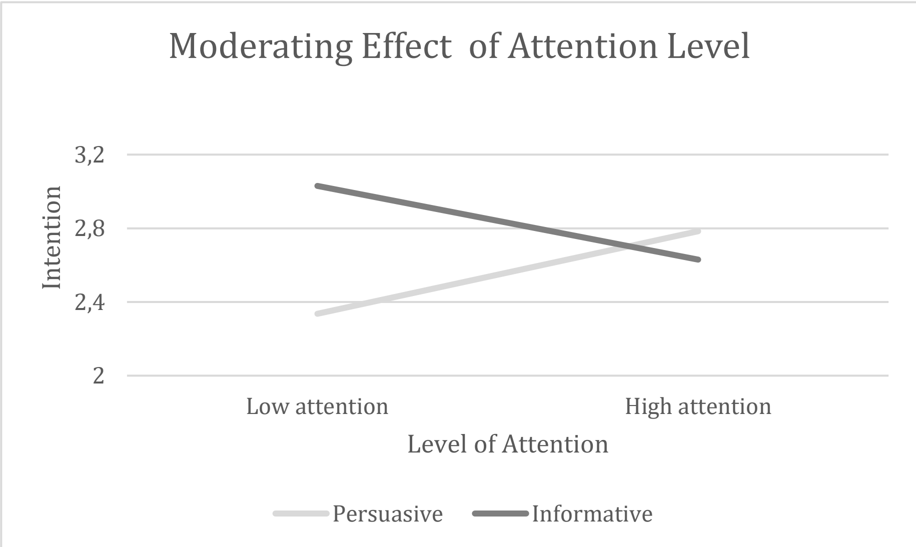
Interestingly, I find a significant coefficient for the *AttentionIndex* as well as a significant interaction term between a customer's attention level and his or her exposure to a persuasive poster, *PersuasivePoster*AttentionIndex*. Because this interaction term is not composed with two binary variables, but one categorical (*PersuasivePoster*) and one continuous (*AttentionIndex*), the interpretation of this variable is slightly different. In that case, the moderation means that the differences between the two groups of the independent variable (type of poster) differ according to the level of the moderating variable (level of attention).

The interaction term tells us the following:

For a subject with an average level of attention, who sees an informative poster, the average *Intention* is 0,270 higher compared to a subject with the same average attention level, who sees a persuasive poster, ceteris paribus (coefficient of *PersuasivePoster*).
However, this gap in intention level is not the same for every subject, it depends on the level of *AttentionIndex* the subject has, as the coefficient of interaction term between poster and attention level (*PersuasivePoster*AttentionIndex*) is significant at a 1% significance level.
A 1-unit increase in *AttentionIndex*, for subjects who see an informative poster, decreases the intention level on average with 0,050 points, whereas for a subject that sees a persuasive poster, a 1-unit increase in *AttentionIndex* increases the intention level with 0,106 point.

In other words, the difference in intention between persuasive and informative posters widens as the level of attention decreases. This relationship becomes understandable in Figure 6, where the "low" attention level represents an attention level of -4, and the "high" attention level represents a +4-attention level, as discussed in the discussion about the creation of the Attention Index Score, *AttentionIndex*.

Figure 6: Interaction between Level of Attention and Type of Poster on Intentions



7.1.5. Conclusion

Conclusively, I can say that the level of attention has a significant moderating effect on the relationship between the type of advertisement poster and customer intentions. For subjects with a relatively high attention level, in general, persuasive posters have a more positive impact on customer intentions, whereas for subjects with a relatively low attention level, informative posters have a more positive impact on customer intentions.

7.2. Attention to different elements

7.2.1 Expectations

In the literature section of this paper, I already discussed what elements are important in advertisement posters. The general finding was that pictures capture more attention than textual elements (Childers, 1986; Decrop, 2007; Scott et al., 2016). A study conducted by Ryu et al. (2009) also found that the pictorial element captured more attention, where attention was defined as looking time and fixations and so the pictorial element had higher viewing time and number of fixations.

Based on these findings, I created my advertisement posters with a textual element and a visual element, which consisted of a picture and the brand logo, as this is also an important attention catcher.

Finding out what elements capture the most attention in an advertisement poster is not part of the main research, I only used the findings in literature as a base to create my advertisement poster. However, little of the research on this was in a B2B context (i.e., with B2B posters), and therefore it would still be interesting to test what elements captured the most attention in this experiment.

7.2.2. Procedure

In order to do this, I look back at the most common measures for attention, as well as what measures were used in the above-mentioned literature. The gaze duration and number of fixations on a specific AOI tend to be highly correlated and are a good indication of recognition and recall (Aribarg et al., 2010). These measures are also used in the study by Ryu et al. (2009), where looking time can also be seen as gaze duration, as it is the sum of fixations on a specific AOI. The average fixation duration per AOI is an indication of depth of processing (Holmqvist et al., 2011).

7.2.3. Results

In Table 16, the mean value for the three mentioned metrics can be found per AOI, as well as the difference between the AOI's per variable. For every metric, I performed a t-test to test whether the differences were significant, and those values can also be found in Table 16. The complete t-test outcomes can be found in Appendix D., Tables 28, 29 and 30.

Table 16: Mean for various attention metrics and their differences [14]

N = 223	Text	Picture	Difference	T-test
Number of Fixations	3,641	3,350	0,291	0,0002***
Gaze Duration	6696,933	4990,278	1706,655	0,000***
Average Fixation Duration	2065,865	1657,135	408,721	0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

7.2.4 Interpretation

All attention metrics are significantly higher for the textual element: the textual element received on average 0,291 more fixations, a single fixation lasted on average 408 milliseconds (0,4 second) longer on the textual element, and in total subjects looked at the text 1706 milliseconds (1,7 second) longer on average compared to the visual element.

7.2.5. Conclusion

As all three metrics lean towards the textual element, I conclude that the textual element (significantly) captured more attention than the visual element. This is interesting, as most literature concludes the contrary, and say that pictures in general capture more attention. This could potentially be due to the industry, as maybe for B2B events, the text is just more relevant for subjects than the picture and logo. It could also have something to do with the subject pool, as a lot of subjects were university students. To make proper conclusions and suggestions, more research would be needed, and these findings provide interesting grounds for this.

7.3. Additional Analyses

Chapter 6, as well as the post-hoc analysis in Chapter 7, have focused on the topic of the thesis, i.e., how different types of advertisements drive customer intentions, and the role the uncertainty level and attention play.

On top of the main analyses discussed, I want to take the opportunity to make some methodological contributions to the literature about the difference between stated and actual attention, i.e., self-reported bias as explained in the methodology section. However, this topic is not part of the main

[14] For this analysis, I chose to look at the 3 metrics separately instead of using an Attention Index Score per AOI, because with the Attention Index, all variables are standardized, where all means are 0 and therefore it is not possible to compare the means anymore.

analysis, and no hypotheses are formed regarding this topic. As I do not want to detract from the flow of reading, I included these additional analyses in Appendices E1 and E2, for every reader that might be interested in these differences between stated and actual attention.

8. Discussion

8.1. Conclusions

In this paper, I studied the effect of different types of advertisement posters (informative and persuasive) on customer intentions towards B2B events. In other words:

"How do different types of advertisements (informative versus persuasive) affect customer intentions towards business-to-business events?"

I explored the moderating role of the level of uncertainty and the mediation role of attention by the use of eye tracking technology. In the Post-Hoc analysis, I studied the moderating role of attention, identified what elements captured the most attention and explored the differences between stated and actual attention, both on the poster and per element. Table 17 contains a summary of the hypotheses, along with an indication of their support status and the reason for this status.

Table 17: Hypotheses summary and conclusion

	Hypotheses	Supported?	Reason
H1A	For customers with a relatively low uncertainty level, persuasive types of advertisements have a stronger positive impact on customer intentions, compared to informative advertisements.	No	Lack of statistical power, however the effect appears to be present
H1B	For customers with a relatively high uncertainty level, informative types of advertisements have a stronger positive impact on customer intentions, compared to persuasive advertisements.	No	Lack of statistical power, however the effect appears to be present
H2	The effect of different types of advertising on customer intentions towards B2B events is mediated by customer attention.	No	No indirect effect found, however found a significant moderating effect

8.1.1. Hypotheses 1A and 1B

The first two hypotheses (1A and 1B) explored the interaction between the type of advertisement poster and the uncertainty level of the customer, and the moderating effect on customer intentions. With a linear regression, I found significant ($p = 0,099$) evidence that the type of poster impacted customer intentions. More specifically, a persuasive poster, regardless of other variables, lowered intentions by 0.3 points on a 5-point Likert Scale, compared to an informative poster. The effect of the level of uncertainty on customer intentions was found to be neglectable and statistically insignificant ($p = 0,933$).

The statistical analysis revealed that the interaction term between type of poster and uncertainty level was insignificant (p = 0,234), and therefore I must conclude that hypotheses 1A and 1B cannot be supported. However, the results suggest that the moderating role of uncertainty may exist though. Specially, it is suggested that for individuals with a low uncertainty level, persuasive posters have a slightly more positive impact on customer intentions compared to informative posters, be that as it may, the difference is small. To the contrary, for those with a higher uncertainty level, informative posters have a much stronger positive effect on intentions than informative posters.

Conclusively, although statistical power limitations prevented the identification of an interaction effect, the results remain interesting because they show an indication of an interaction, and it can be inferred that depending on the uncertainty level, either persuasive or informative posters will probably have a stronger positive impact on customer intentions towards B2B events.

8.1.2. Hypotheses 2

Hypothesis 2 explored the potential mediating role of the level of attention on the relationship between type of poster and intentions. Despite that fact that previous literature provided evidence to explore this relationship (Goodrich, 2011; Pechmann & Stewart, 1990), the results from my study did not show any evidence of the existence of this mediating role of attention. The reason was the lack of an indirect effect: the effect of *PersuasivePoster* on *AttentionIndex,* and the effect of *AttentionIndex* on *Intention,* i.e., path a x b (Figure 5), was very small and insignificant. The results do show a total and direct effect, i.e., path c and c', proving that the type of poster does impact customer intentions, a conclusion also drawn in the analysis of hypotheses 1A and 1B.

8.1.3. Post-Hoc analysis

Following up on the lack of statistical evidence of the mediating role of attention, because the type of poster did not influence attention, I investigated the potential moderating role of attention. The results reveal a significant interaction between poster type and attention, implying that depending on the level of attention, the effect of posters on customer intentions vary across different posters. More specifically, when the attention level is relatively high, persuasive posters seem to be more effective in increasing customer intentions, while informative posters have a stronger positive impact on customer intentions when the attention level is relatively low. This interaction is significant at a 1% significance level.

Post-Hoc analyses also indicate that, on average, subjects paid considerably more attention to the textual element of the poster compared to the visual element, contradicting existing literature which typically suggests that more attention is given to the visual element of an ad.

8.2. Significance of the research

My study reinforces findings from previous research (Narayanan et al., 2003 & 2005) on how the level of uncertainty plays a moderating role in the effect of advertisements on advertisement effectiveness (*Intention* in my study), however adds to the existing literature by examining the effect of different <u>types</u> of ads, and not only the <u>role</u> of advertising.

This study applies theories from previous studies about the mediating role of attention (Goodrich, 2011), but uses eye tracking as a measure for attention to overcome self-reported bias. It also assessed the role of attention in a study where the independent variable is the type of advertisements, which were informative or persuasive, also not yet tested.

Not only are these concepts never researched together in one study, but the research is also conducted in a not yet well-researched industry, the B2B event industry. With this, relevant suggestions can be made about the type of ad should be used in the advertising of B2B events.

8.3. Implications

The analyses performed in this research paper allow me to make suggestions for B2B advertising that could be applied in practice. In situations where an adviser is aware that their target customers have a high level of uncertainty, it is advisable to provide them with information about an event rather than attempting to persuade them to attend the event. For instance, providing information about the price, location and date can help enhance the informativeness of a poster. This strategy will increase the likelihood of their attendance. To the contrary, when you know that your customers have a low level of uncertainty, for example when sending an invitation to previous attendees, it would be better to use a persuasive type of ad to augment their intentions to attend the event. You could use emotional appeals such as “Do not miss out” or “Very fun and educational” to enhance a poster’s persuasiveness.

Concerning the advertisement itself, it appears that for B2B events, textual elements capture more attention than visual elements. Thus, when advertisement space is limited, it is recommended to allocate more space to text than pictures in the advertisement poster.

Moreover, in case an advertiser has prior knowledge that little attention will be paid to the advertisement, such as in the case of advertising on a roadside billboard, one should preferably focus on informative ads rather than persuasive ads. On the other hand, when an adviser anticipates that the advertisement will receive relatively much attention, for instance when advertising in an industry magazine, it is recommended to advertise with a more persuasive type of ad. For one because the attention level will probably be high, and two because the uncertainty level of industry magazine subscribers will probably be relatively low as well.

8.4. Limitations

Even though interesting suggestions can be made for the B2B event industry, it must be done with caution as this study does have some limitations. For one, the manipulation of the level of uncertainty was not very successful, as the difference between subject's indicated uncertainty levels were small, as well as insignificant. Therefore, it is difficult to make serious suggestions based on one's uncertainty level.

Also, even though for the analysis of hypothesis 2, I did not only rely on self-reported data (as the measure of attention with eye tracking is a true representation of one's attention), the dependent variable *Intention* is still based on self-reported data. Therefore, I have only partially overcome self-reported bias. However, the experimental design guarantees randomization, which at least solve the correlational nature of self-reports.

The sample size is rather small, which leads to low statistical power. The sample is also not a true representation of the population, as most subjects were students with an age between 18 and 23. The results often show a significant coefficient of age, indicating that age and intention are positively correlated (Table 12, Table 15 and Table 24). If the age of the sample would be higher, i.e., a truer representation of the population, the effect on customer intentions might be different.

Finally, the coefficients of the dummy variables for event types show some variation between events. In the regression output for hypotheses 1A and 1B can be seen that on average, *Intention* increased by 0,284 points when the advertised event was a workshop compared to a festival (reference event) (p = 0,104) and decreased by 0,279 points (p = 0,142) when the poster advertised a product launch. In other words, the suggestions made cannot be generalized for every B2B event, as customer intentions differ between events and with that, the external validity of the study is low.

8.5. Future research

There are endless possibilities for future research. First, it could be interesting to see how the experiment would play out with a larger, and more representable sample. In that case, the relationship between age and customer intentions could be explored more. If the experiment would be repeated, the manipulation of the uncertainty level should be stronger, and assess whether this would lead to a stronger interaction between the level of uncertainty and type of poster (and reaching statistical significance). I have also seen that the type of event plays a role in the increase of customer intentions. Instead of different types of posters as independent variable, a study could be conducted where the independent variable is the type of event, and test what role the uncertainty level and level of attention would play in this relationship on customer intentions. This would allow researchers to make more specific suggestions that can be applied in practice, as the results from this study are not generalize for all events.

One of the limitations of this study is that the dependent variable relies on self-reported data, as I have only asked the subjects how likely they would be to attend the event, a hypothetical question. A more extreme version of the experiment could be conducted, where instead of measuring customer intentions, you could measure actual attendance to the event. In that case, a field study must be conducted, which on the one hand comes with a lot of challenges, but on the other hand increases validity.

The eye tracking technology also offers opportunities to perform more elaborate research. In this study, only two Area's of Interest were used, and the posters were kept relatively simple. In the post-hoc analysis, I found that the textual element captured more attention than the visual element. In a future study, more AOI's can be created, allowing the researcher to also measure what roles the different elements fulfill, and why in this industry, and not like most others, the textual element captures more attention than the visual one.

Conclusively, this research paper offers plenty of ground for the B2B event industry, combined with varying uncertainty levels and different types of posters, to be further researched. It is evident that the level of attention paid plays a role in the effectiveness of advertisements, and to make valuable suggestions for this industry, as well as potentially other industries, a plethora of research directions can be explored in the future.

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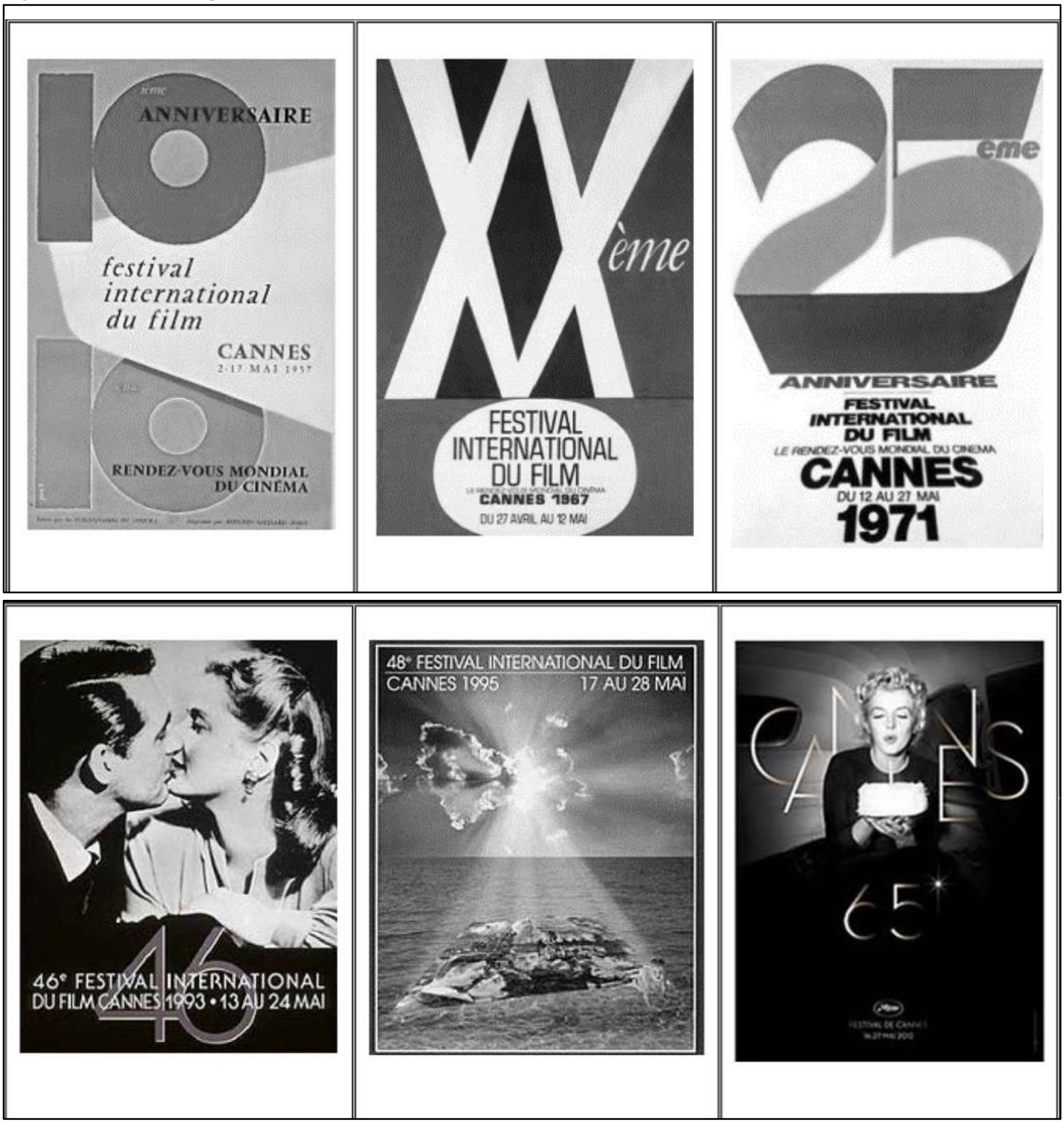
10. Appendices

10.1. Appendix A – Literature Section

Figure 7 – Collection of posters from the Cannes Festival (source: Sel & Aktas, 2019)



10.2. Appendix B – Methodology Section

B.1. Experimental Flow

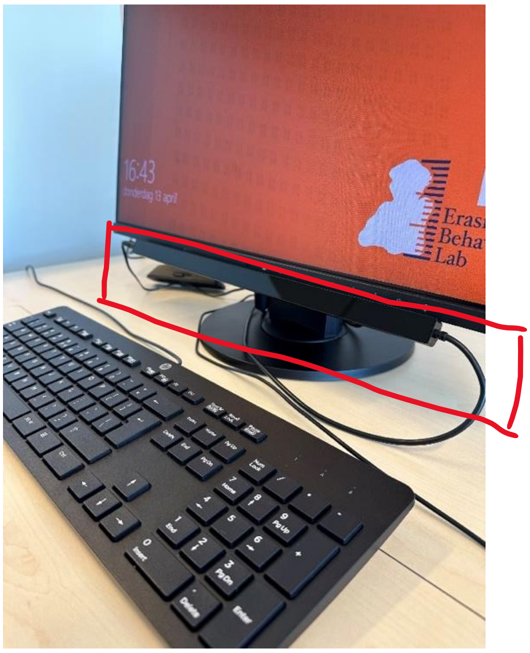
Figure 8: Experimental Flow of the Eye Tracking Study

B.2. Eye tracking procedure

The Behavioral Lab is located at the 12th floor of the Mandeville Building. With a code, I can get the key that provides me access to the Eye Tracking Lab. This lab is a small room with two desks with computers, separated by a partition wall (Figure 9). When the subject is seated in front of the right computer (A), the researcher (me) is able to start to experiment on the left screen (B). The two screens are synchronized, so the researcher can see what the subject sees and does. However, the subject answers all questions by him or herself with their mouse.

Figure 9: Set up Tobii Eye Tracking Lab

Figure 10: Tobii Eye Tracking on computer



The Eye Tracking is placed below the computer screen, and it barely noticeable for the respondent (Figure 10). After answering the general questions, the calibration is started by the researcher by clicking the space bar and the subject is instructed to follow the dot (Figure 11). The output is shown on both screens (Figure 12), and the researcher can decide whether to accept the calibration or to recalibrate.

Figure 11: Calibration ongoing

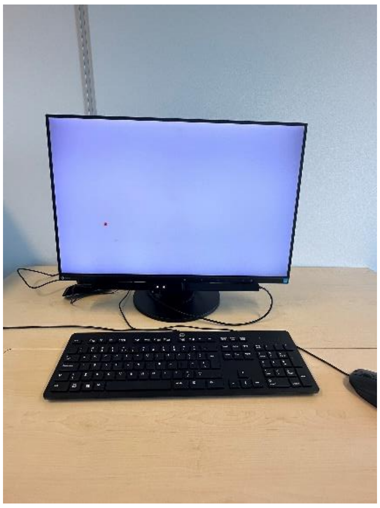
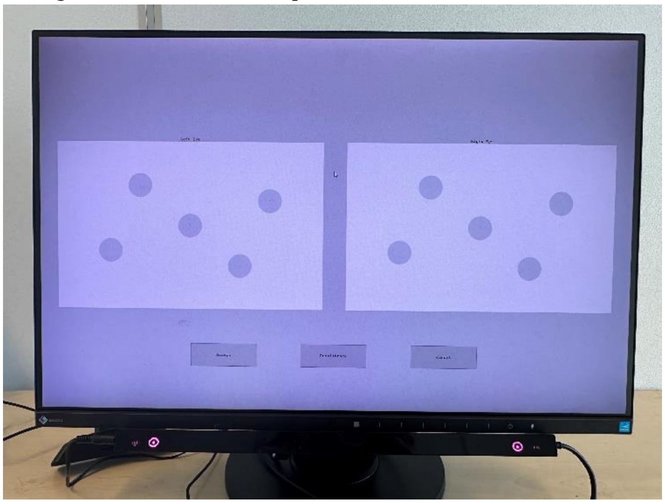


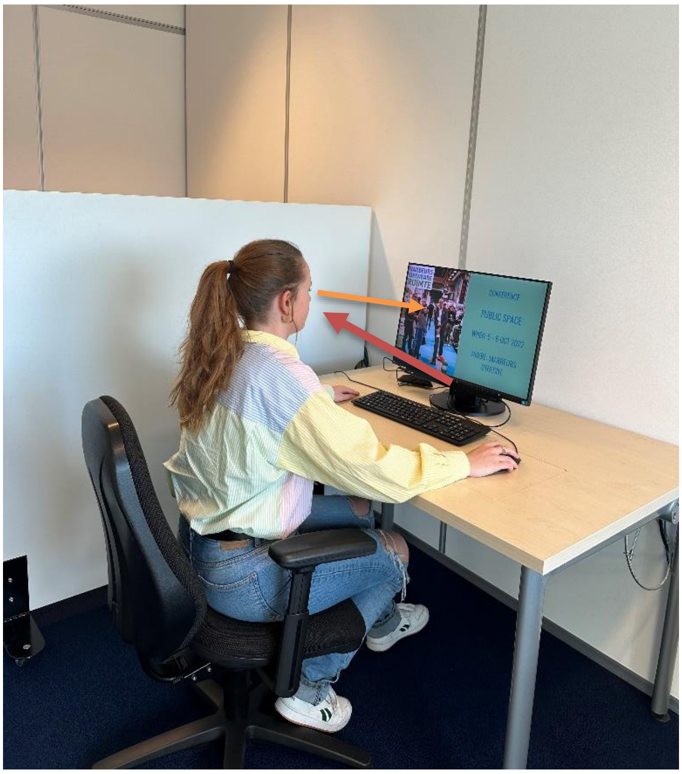
Figure 12: Calibration output



The subject can control the rest of the experiment, when he or she is finished looking at the poster the subject can click the mouse to go to the questions.

As can be seen in Figure 13, the poster fills the entire screen and the eye tracker under the screen tracks only when the stimulus is on the screen. When the subject is answering questions, no eye tracking is going on.

Figure 13: Subject looking at the poster while Eye Tracker is tracking



B.3. Experiment questions and text

The experiment starts with an introduction:

"Welcome to my experiment for my Master Marketing, and thank you in advance for your participation.

In a moment, you will first be asked to answer some general questions. After that, there will follow an Eye Tracking study, where you will be asked to look at a number of posters, followed by some questions. The experiment will take approximately 15 minutes.

Please note that your participation will remain anonymous, and the information will only be shared with a select group of people.

During this experiment, if you are ready to go to the next page click the mouse¨

This is followed by general questions, and with the following answer options:

1. Gender (male, female, other, rather not say)
2. Age (under 18, 18 – 23, 24 – 29, 30 – 35, over 35)
3. Highest level of education (Primary school, High school, Bachelor, Master, PhD)
4. Years of job experience (under 1, 1 to 5, 6 to 10, 11 to 15, 16 to 20, over 20)
5. Familiarity with B2B events (5-point scale from nothing to a lot)

After this, the calibration will begin. It is introduced and explained with the following text:

¨Before we begin the experiment, it is necessary to calibrate the eye tracker.
In order to do this, a dot will be shown on the screen.
You have to follow the dot with your eyes.
Look at the black dot in the middle.

Click the mouse to start. ¨

The calibrator uses five calibration points. After the calibration, I judge whether the calibration is good enough. If no, I ask the program to recalibrate, and if yes, I accept the calibration.

The subject will get some extra instructions about the experiment and the fixation that will happen in between the different posters:

¨We are now going to start the experiment.

In each trial you will see a black fixation cross.
Please look at the fixation cross and when a green box appears, the trial will start.

An advertisement poster will be shown.
Please click the mouse if you finished looking at the poster.

Click the mouse to continue. ¨

Each of the four events will be introduced with little or a lot of information, i.e., the respondents have a high or low uncertainty level before they look at the advertisement poster (Appendix B.4). Then, the fixation cross will appear in order to find the subject's eyes again in order to track their movement. The posters will be shown (Appendix B.5) and finally, the following questions will be asked:

1. After seeing the advertisement poster, how likely would you be to attend this event? (1 = not likely at all, 5 = very likely)
2. On a scale of 1 – 5, how much did the poster capture your attention? (1 = not at all, 5 = very much)
3. Which element captured the most attention (answer possibilities: picture of text)
4. Indicate on a scale from 1 – 5, how much do you agree with the following statement: Before I saw the poster, I felt uncertain about attending the event
(1 = completely disagree, 5 = completely agree)
5. Indicate on a scale from 1 – 5, how much do you agree with the following statement: I feel that the ad provides a lot of information about the event
(1 = completely disagree, 5 = completely agree)

This process, from the introduction text to the questions about the poster repeats itself four times, for four different events.

After that, the experiment end with the following text:

¨*Thank you for taking part in this experiment!*

Goodbye! ¨

B.4. Introductory text of all events

Event 1 – Conference

Low uncertainty
Imagine you work for the city council and you are working on a project to improve the public space in your city (think about street lighting, playgrounds, parking spaces etc.). Every year, there is a conference ‘Vakbeurs Openbare Ruimte’, that has stands will all sorts of suppliers that have to do with the public space. You have visited the event in the last three years as well, and this year you are wondering whether to visit it again.

Click your mouse to look at the advertisement poster.

High uncertainty
Imagine you work for the city council to improve the public place in your city (think about street lighting, playgrounds, parking spaces etc.). This year, there is a new conference ‘Vakbeurs Openbare Ruimte’, that has stands will all sorts of suppliers that have to do with the public space. Given this is a new conference, you have never visited this event. You are wondering whether to visit it.

Click your mouse to look at the advertisement poster

Event 2 – Product launch

Low uncertainty
Imagine you are working for a phone store, and this store sells lots of different phones from different brands. You want to expand the range of models the store offers, that also includes the brand i.safe MOBILE, a company that targets customers in the industry as their phones are explosion proof.

You are well aware of the i.safe MOBILE brand and have visited some of their prior product launches. You know they are organizing a launch of their newest model and are curious about this new model. Yet, you wonder if it is worthwhile to visit the launch or if you can simply do some research online…

Click your mouse to look at the advertisement poster

High uncertainty
Imagine you are working for a phone store, and this store sells lots of different phones from different brands. You want to expand the range of models the store offers. There is a new brand on the market, called i.safe MOBILE, a that targets customers in the industry and claims their phones are explosion proof.

You are not yet familiar with the brand i.safe MOBILE. You know they are organizing a launch of their newest model and are curious about this new model. Yet, you wonder if it is worthwhile to visit the launch or if you can simply do some research online…

Click your mouse to look at the advertisement poster
Event 3 – Workshop

Low uncertainty
Imagine you are part of the IT team of a big consultancy firm, and daily you are working on the cloud security of the company. Since a while, you are using Microsoft Cloud Security app, but you are still struggling with it.

Multiple colleagues have told you about a workshop they attended at Microsoft, to gain more knowledge of the program. You are considering participating in this workshop as well.

Click your mouse to look at the advertisement poster.

High uncertainty
Imagine you are part of the IT team of a big consultancy firm, and on a daily basis you are working on the cloud security of the company. Since a while, you are using Microsoft Cloud Security app, but you are still struggling with it.

Microsoft organizes a workshop about this Cloud Security app, but you did not know anybody that already attended this workshop. You are considering participating in this workshop.

Click your mouse to look at the advertisement poster.

Event 4 – Festival

Low uncertainty
Imagine you are a manufacturer of electronic bikes. Your bikes are sold in multiple stores, but you want to get more buyers and you also want to learn more about the industry to improve your design. The past 2 years, you have attended the bike industry festival, where both manufacturers and buyers come together to discuss new trends in the industry. You are wondering whether you should attend the festival again this year.

Click your mouse to look at the advertisement poster.

High uncertainty
Imagine you are a manufacturer of electronic bikes. Your bikes are sold in multiple stores, but you want to get more buyers and you also want to learn more about the industry to improve your design. You come across a bike industry festival, where both manufacturers and buyers come together to discuss new trends in the industry. This event is new to you. You are wondering whether you should attend the festival.

Click your mouse to look at the advertisement poster.

B.5 - Collection of experiment posters

Figure 14: Informative poster Conference

Figure 15: Persuasive poster Conference

Figure 16: Informative poster Product Launch

Figure 17: Persuasive poster Product Launch

Figure 18: Informative poster Workshop

Figure 19: Persuasive poster Workshop

Figure 20: Informative poster Festival

Figure 21: Persuasive poster Festival

B.6. Additional variables overview

Table 18: Overview of all variables generated during the analyses

Name of variable	Type of Variable	Clarification
EventConference	Binary variable	0 = the event is not a conference and 1 = the event is a conference
EventProductLaunch	Binary variable	0 = the event is not a product launch and 1 = the event is a product launch
EventWorkshop	Binary variable	0 = the event is not a workshop and 1 = the event is a workshop
EventFestival	Binary variable	0 = the event is not a festival and 1 = the event is a festival
PersuasivePoster* UncertaintyLow	Binary variable	The interaction term between PersuasivePoster and UncertaintyLow, 1 = persuasive poster and low uncertainty level, 0 otherwise
z1ViewingTime	Continuous variable	Standardized variable of Viewing Time
z2NOFTotal	Continuous variable	Standardized variable of Number of Fixations on the entire poster
z3GDTotal	Continuous variable	Standardized variable of Gaze Duration on the entire poster
z4AFDTotal	Continuous variable	Standardized variable of the Average Fixation Duration on the entire poster
AttentionIndex	Continuous variable	Indicating how much attention a subject paid to the poster, which is the sum of 4 standardized variables that indicate attention (z1ViewingTime, z2NOFTotal, z3GDTotal and z4AFDTotal)
PersuasivePoster* AttentionIndex	Continuous variable	The interaction term between PersuasivePoster and AttentionIndex, ranging from -6,177 to 7,586
ViewingTime4	Continuous variable	Variable ViewingTime, but rescaled on a 0 – 4 scale
NOFTotal4	Continuous variable	Variable NOFTotal, but rescaled on a 0 – 4 scale
GDTotal4	Continuous variable	Variable GDTotal, but rescaled on a 0 – 4 scale
AFDTotal4	Continuous variable	Variable AFDTotal, but rescaled on a 0 – 4 scale
AttentionIndex4	Continuous variable	The sum and average of the variables ViewingTime4, NOFTotal4, GDTotal4 and AFDTotal4
NOFText1	Continuous variable	Variable NOFText, but rescaled on a 0 – 1 scale
GDText1	Continuous variable	Variable GDText, but rescaled on a 0 – 1 scale

AFDText1	Continuous variable	Variable AFDTotal, but rescaled on a 0 – 1 scale
AttentionText1	Continuous variable	The sum and average of the variables NOFText1, GDText1 and AFDText1
NOFPicture1	Continuous variable	Variable NOFPicture, but rescaled on a 0 – 1 scale
GDPictutre1	Continuous variable	Variable GDPicture, but rescaled on a 0 – 1 scale
AFDPicture1	Continuous variable	Variable AFDPicture, but rescaled on a 0 – 1 scale
AttentionPicture1	Continuous variable	The sum and average of the variables NOFPicture1, GDPicture1 and AFDPicture1
AttentionActualElement	Binary variable	Variable taking the value of 1 if AttentionText1 > AttentionPicture1, and 0 otherwise

B.7 – Eye tracking Methodology: Additional Details

In eye tracking, not everything is a fixation. The eye can move very rapidly, and sometimes the eye is already at a certain point and moved on from it before the brain can actually process what it has seen. If that is the case, a person does not actually pay attention and therefore it is important to separate these situations from actual fixations.

B.7.1. Definitions

I will start by explaining a few eye tracking definitions, and afterwards I will discuss literature that support my decision on what a fixation is and what is not a fixation.

1. Saccade: saccades are considered to be one of the most rapid movements of the human eye. It actually is the movement between fixations, the motion from one fixation to the other (Salvucci & Goldberg, 2000). During a saccade, we are considered to be blind as the motion is that rapid, and therefore no actual processing takes place (Holmqvist & Andersson, 2017, page 23). Saccades typically take 30 – 80 milliseconds to complete.
2. Glissade: a glissade is the "wobble" when the eye arrives at the Area of Interest, but the time it needs to make the stop, and before the actual processing starts. Another word is the post-saccade movement, and it usually takes 10 – 40 milliseconds to complete (Holmqvist & Andersson, 2017, page 23).
3. Fixation: according to Salvucci & Goldberg (2000), fixations are "pauses over informative regions of interest". In other words, a fixation is not a movement, it is the period the eye remains at a certain point (Holmqvist & Andersson, 2017, page 22). In general, when researchers measure a fixation, they also measure the attention to that point, even though attention and fixations do not always go hand in hand (Holmqvist & Andersson, 2017, page 379). However, for simplicity, most studies do assume that a fixation translates to attention and that is why I also do this in my research.

B.7.2. Determination of Minimum Fixation Duration

When the Tobii Eye Tracker samples and thus measures where the eye is, not everything can automatically be considered to be a fixation. Because for example, when the eye is on the border between the textual and the visual element, it could be that the eye is sometimes on the picture and sometimes on the text, as the eye is never completely still. Therefore, we need a minimum fixation duration, otherwise it will count all these switches as separate fixations without the subject actually consciously looking at either of the AOI's.

The minimum fixation duration varies between studies, there is not one minimum that is agreed upon and every researcher uses. I looked at various advertising studies to determine the appropriate minimum fixation duration.

In a study where the researchers used direct and indirect printed advertisement posters, the minimum fixation duration was 80 milliseconds (Simola et al., 2020). In another study by Rosbergen, Pieters and Wedel (1997), they used 100 milliseconds when testing with printed static ads.

In most studies, the minimum fixation durations are around 100 to 200 milliseconds, because you want to exclude glissades and saccades as these are not actual fixations (Nyström & Holmqvist, 2010). Hooge et al. (2022) explain: "Fixations shorter than 100 ms are removed because it has thought that the decision to move on (saccade away for a word) could not have been guided by visual processing during such a short fixation)".

Based on this information, I decided to go for a minimum fixation duration of 100 milliseconds. The study by Simola et al. (2020) uses 80 milliseconds, and as it often also takes another 10-40 milliseconds to actually start processing (i.e., glissades) I think a minimum of 100 milliseconds is fair.

B.7.3. Additional Settings

To analyze the eye tracking data, some additional settings needed to be determined, when samples in between fixations are not at the AOI for a very short period. For example, somebody looks at the AOI for 60 milliseconds, then looks away for a few milliseconds, and then looks back at the same AOI for another 60 milliseconds. Is this a fixation or not?

Normally, the settings to determine a fixation are 20/4/20. This means that when the first fixation lasts <u>at least</u> 20 cycles (i.e. 80 milliseconds, as 1 cycle is 4 milliseconds at a 250 Hz sampling rate), and this is followed by <u>not more than</u> 4 samples (16 milliseconds) not at that specific AOI, followed by a fixation of again <u>at least</u> 20 samples (80 milliseconds), this is all considered to be 1 big fixation. But when the time in between is longer than 16 milliseconds, the fixations are separated.

However, I decided to have a minimum fixation duration of 100 milliseconds, and therefore the settings need to be changed. 20 cycles are changed to 25 cycles (100 / 4 = 25) and to follow the same ratio, the settings are **25 / 5 / 25.**

The goal of this setting is to not count fixations separately when they are actually one big fixation with a small pause. Below are some examples to clarify when and how fixations are calculated:

Example 1

- 30 samples on AOI 1
- 3 samples on AOI 2
- 40 samples on AOI 1

→ 1 Fix of 73 samples on AOI 1
Because 3 < 5

Example 2

- 18 samples on AOI 1
- 3 samples on AOI 2
- 40 samples on AOI 1

→ 1 Fix of 40 samples on AOI 1
Because 18 < 25

Example 3

- 35 samples on AOI 1
- 6 samples on AOI 2
- 60 samples on AOI 1

→ 2 fixations on AOI 1
F1: 35 samples
F2: 60 samples
Because 6 > 5

B.7.4. Interesting references

The methodology explained and used in this paper is just the tip of the iceberg when it comes to eye tracking. There are many more metrics available, as well as an ongoing discussion about what should or should not be measured as a fixation.

Because this is a Master Thesis, I could not go into the details too much, but in case one is interested, below I have referenced some interesting sources that can be used when you want to explore eye tracking in more detail:

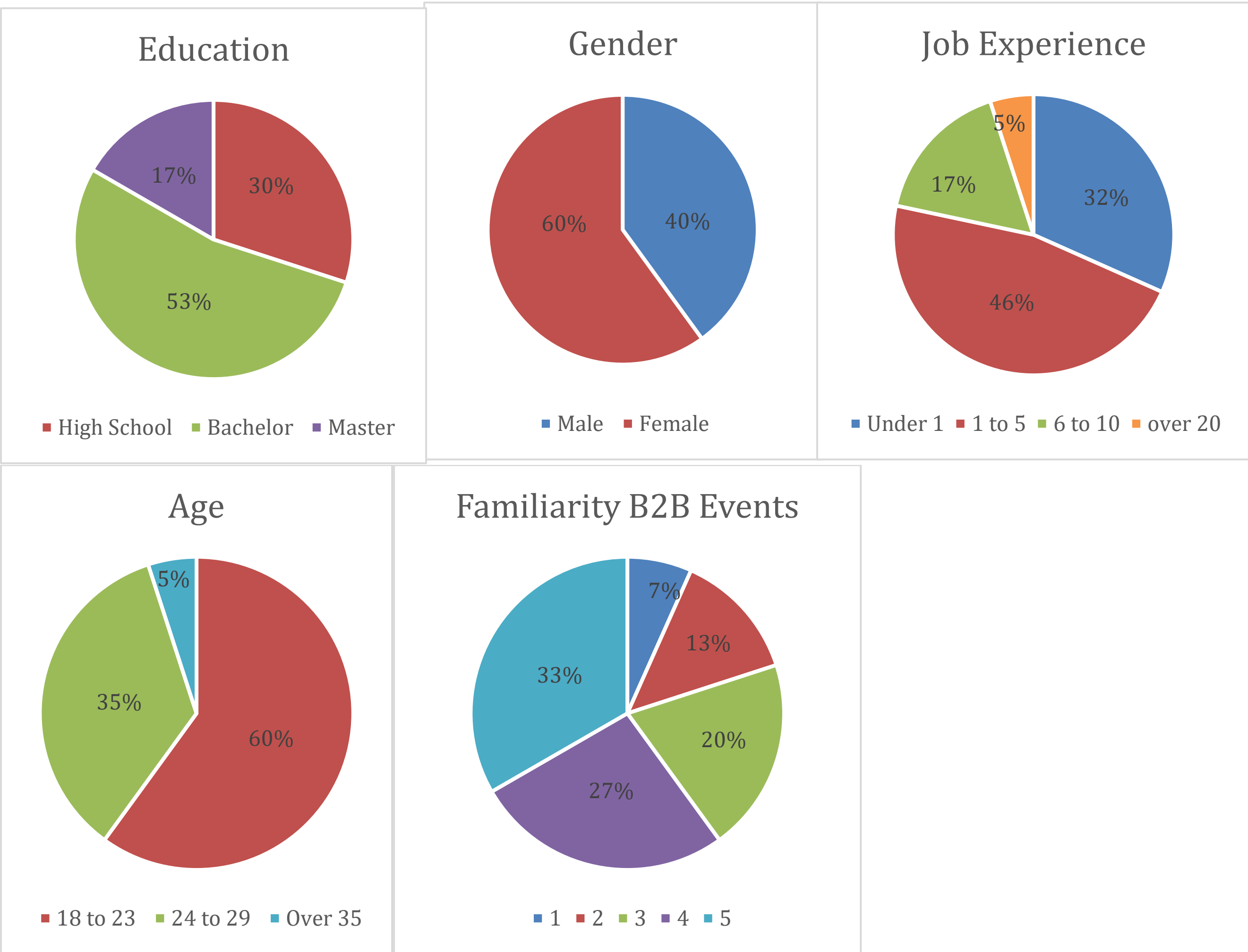
1. The book “Eye Tracking: A comprehensive guide to methods and measures” by Holmqvist and Nystrom is very useful and explains all eye tracking technology in detail. The book is also referred to as “the bible in eye tracking”, it provides a lot of information about metrics, data recoding etc.
2. Pieters & Wedel are two marketing researchers that are very experienced with eye tracking and use it a lot in their research. All papers written by them are good, below some examples:
    a. Wedel, M., & Pieters, R. (2008). Eye tracking for visual marketing. *Foundations and Trends® in Marketing*, *1*(4), 231-320.
    b. Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing*, *68*(2), 36-50.
    c. Wedel, M. (2013). Attention research in marketing: A review of eye tracking studies. *Robert H. Smith School Research Paper No. RHS*, *2460289*.
3. Chapter 6 of the book Managing Economic Innovations – Methods and Instruments by Białowąs & Szyszka (2019) explains the use of eye tracking in an understandable matter.

10.3. Appendix C – Results Section

C.1 Descriptive Statistics

C.1.1. Descriptives General Information

Figure 22: Pie Charts representing the distribution of general variables



C.1.2. Descriptives Eye Tracking Data

C.1.2.1. Reason for dropped observations

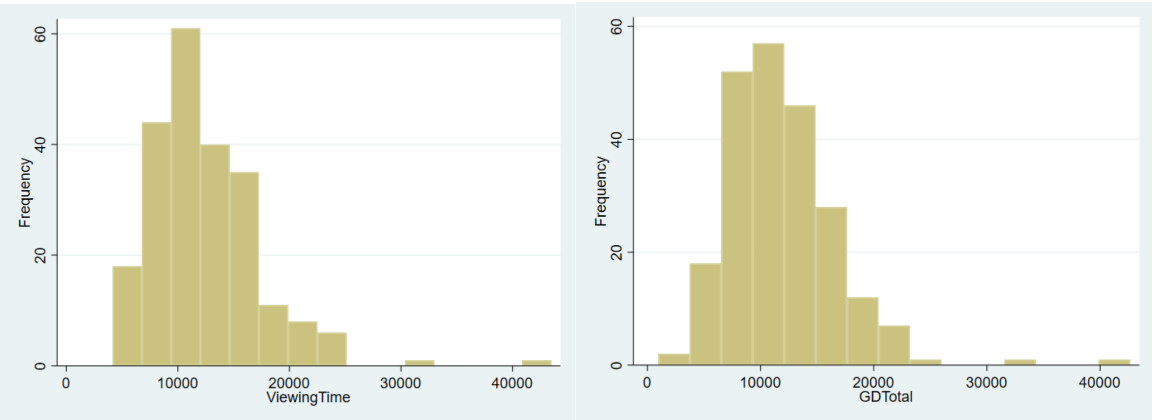
Of the 240 observations, 17 were dropped from my sample. The first reason is that certain fixations were not correctly timed from the start (15 observations). In this case, the Gaze Duration for a certain AOI, either picture or text, within a trial were much higher than the Total Viewing time, which is technically impossible, because it would mean that a person looked longer at the text or picture than the poster in total, where both are on.

When I went back to the raw data, where you can find the duration of every separate fixation, I could see that the almost in all situations, the final fixation on a poster took extremely long, sometimes up to

90.000 milliseconds, which is 1,5 minute, while the poster was only on the screen for 14.565 milliseconds (14 seconds). This is probably because the eye tracker lost the subject's eye for a while, since that can be seen in the raw data as well.
In total, I found 15 of these outliers where the Gaze Duration was longer than the Viewing Time, and because this is impossible, I dropped these observations from the sample when using the eye tracking data.

The second reason, why 2 other observations were dropped, is because they were clearly outliers in the dataset. As can be seen in Figure x, two observations had a much higher viewing time than the others, 32592 and 43469 milliseconds. This resulted in the same 2 outliers in the Gaze Duration, and therefore I decided to drop the 2 observations from the dataset.

Figure 23: Histogram Distribution of Viewing Time and Total Gaze Duration



C.1.2.2. Descriptives Eye Tracking

Table 19: T-test to test the difference in Gaze Duration between Text and Picture

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
GDText	223	6696,933	183,699	2743,211	6334,916	7058,95
GDPicture	223	4990,278	125,851	2282,558	4889,053	5291,503
Difference	223	1706,655	198,512	2964,416	1315,446	2097,864

Mean (diff) = mean (GDText – GDPicture)		t = 8,5972
H0: mean (diff) = 0		Degrees of freedom = 222
Ha: mean (diff) < 0 p = 1,000	Ha: mean (diff) = 0 p = 0,000	Ha: mean (diff) > 0 p = 0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

C.2. Manipulation Checks

Table 20: T-test Manipulation check Information Level

N = 240	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
Subjects with informative poster	120	3,025	0,104	1,141	2,819	3,231
Subjects with persuasive poster	120	1,917	0,084	0,922	1,750	2,083
Combined	240	2,471	0,076	1,175	2,321	2,620
Difference		1,108	0,134		0,845	1,372

diff = mean (subjects with informative poster) – mean (subjects with persuasive poster)	t = 8,276	
H0: diff = 0	Degrees of freedom = 238	
Ha: diff < 0 p = 1,000	Ha: diff = 0 p = 0,000	Ha: diff > 0 p = 0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Table 21: T-test Manipulation check Uncertainty Level

N = 240	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
Subjects with high uncertainty level	120	2,942	0,097	1,063	2,749	3,134
Subjects with low uncertainty level	120	2,8	0,095	1,042	2,612	2,988
Combined	240	2,871	0,068	1,053	2,737	3,005
Difference		0,142	0,136		-0,126	0,409

diff = mean (subjects with high uncertainty level) – mean (subjects with low uncertainty level)	t = 1,042	
H0: diff = 0	Degrees of freedom = 238	
Ha: diff < 0 p = 0,851	Ha: diff = 0 p = 0,298	Ha: diff > 0 p = 0,149

C.3. Control Checks

Table 22: Correlations between various variables

Variable 1	Variable 2	Correlation
JobExperience	Familiarity	0,356
Age	Familiarity	0,527
Age	Intention	0,170
Age	Education	0,467
Age	JobExperience	0,506
Familiarity	Intention	0,009
JobExperience	Intention	-0,009
Education	Intention	0,053
Gender	Intention	-0,015

C.4. Hypotheses 1A and 1B

Table 23: Regression output without rounding the coefficients

Intention	Coefficient	Standard Error	T	P-value	95% Confidence Interval	
PersuasivePoster	-0,3022953	0,182	-1,66	0,099*	-0,662	0,057
PersuasivePoster*UncertaintyLow	0,3242932	0,272	1,19	0,234	-0,211	0,860
UncertaintyLow	-0,0143776	0,171	-0,08	0,933	-0,352	0,323
Age	0,2594162	0,097	2,68	0,008***	0,069	0,450
EventConference	-0,1161874	0,183	-0,63	0,526	-0,477	0,245
EventProductLaunch	-0,2788597	0,189	-1,47	0,142	-0,651	0,094
EventWorkshop	0,2842918	0,175	1,63	0,105	-0,060	0,628
Constant	2,328483	0,287	8,13	0,000***	1,764	2,893

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Number of Observations	240
F statistic (4, 235)	3,09
Prob > F	0,0039
R-squared	0,0881
Root MSE	0,99473

Table 24: Results Mixed Model with Random Intercept

Intention	Coefficient	Standard Error	Z – value	P- value	95% Confidence Interval	
PersuasivePoster	-0,277	0,176	-1,57	0,116	-0,623	0,068
PersuasivePoster*UncertaintyLow	0,274	0,259	1,06	0,290	-0,233	0,782
UncertaintyLow	0,011	0,176	0,06	0,952	-0,334	0,356
Age	0,256	0,100	2,56	0,010***	0,060	0,451
EventConference	-0,117	0,169	-0,69	0,488	-0,448	0,214
EventProductLaunch	-0,281	0,169	-1,66	0,096*	-0,613	0,050
EventWorkshop	0,283	0,169	1,67	0,095*	-0,049	0,614
Constant	2,326	0,289	8,05	0,000***	1,760	2,892

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Number of Observations	240
Number of Groups	60
Observations per Group	Min = 4, Average = 4, Max = 4
Wald Chi2(5)	22,58
Prob > chi2	0,0020

C.5. Hypothesis 2

Table 25: Output Sobel-man Mediation tests

	Estimate	Standard Error	Z – value	P- value
Sobel	0,002	0,017	0,146	0,864
Aroian	0,002	0,021	0,116	0,908
Goodman	0,002	0,011	0,228	0,819

	Estimate	Standard Error	Z – value	P – value
a coefficient	-0,709	0,549	-1,291	0,197
b coefficient	-0,003	0,023	-0,147	0,883
Indirect effect a x b	0,002	0,017	0,146	0,884
Direct effect c’	-0,277	0,188	-1,474	0,141
Total effect	-0,275	0,187	-1,470	0,142

Proportion of total effect that is mediated	-0,009
Ratio of indirect to direct effect	-0,009
Ratio of total to direct effect	0,991

Table 26: Bootstrapping mediation output without percentiles

	Observed coefficient	Bootstrap Standard Error	Z – value	P – value	Normal based 95% Confidence Interval	
Indirect effect	0,002	0,018	0,13	0,896	-0,034	0,039
Direct effect	-0,277	0,188	-1,48	0,140	-0,645	0,091
Total effect	-0,275	0,186	-1,48	0,139	-0,639	0,090

Table 27: Bootstrapping mediation output with percentiles

	Observed coefficient	Bias	Bootstrap Standard Error	95% Confidence Interval		
Indirect effect	0,002	0,0002	0,018	-0,034 -0,026	0,045 0,054	P* BC**
Direct effect	-0,277	-0,007	0,188	-0,641 -0,638	0,097 0,109	P BC
Total effect	-0,275	-0,007	0,186	-0,638 -0,635	0,072 0,073	P BC

*P = percentile

*BC = bias-corrected

10.4 Appendix D – Post – Hoc Analysis

Table 28: T-test to test the difference in Number of Fixations between Text and Picture

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
NOFText	223	3,641	0,116	1,726	3,413	3,869
NOFPicture	223	3,50	0,096	1,431	3,161	3,539
Difference	223	0,291	0,082	1,227	0,130	0,453

Mean (diff) = mean(NOFText – NOFPicture)	t = 3,5484	
H0: mean (diff) = 0	Degrees of freedom = 222	
Ha: mean (diff) < 0 p = 0,9998	Ha: mean (diff) = 0 p = 0,0005***	Ha: mean (diff) > 0 p = 0,0002***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Table 29: T-test to test the difference in Gaze Duration between Text and Picture

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
GDText	223	6696,933	183,699	2743,211	6334,916	7058,95
GDPicture	223	4990,278	125,851	2282,558	4889,053	5291,503
Difference	223	1706,655	198,512	2964,416	1315,446	2097,864

Mean (diff) = mean (GDText – GDPicture)	t = 8,5972	
H0: mean (diff) = 0	Degrees of freedom = 222	
Ha: mean (diff) < 0 p = 1,000	Ha: mean (diff) = 0 p = 0,000	Ha: mean (diff) > 0 p = 0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

Table 30: T-test to test the difference in average fixation duration between Text and Picture

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
AFDText	223	2065,865	65,506	978,221	1936,761	2194,95
AFDPicture	223	1657,135	64,357	961,058	1530,305	1783,964
Difference	223	408,721	84,007	1254,493	243,168	574,274

Mean (diff) = mean (AFDText – AFDPicture)	t = 4,855	
H0: mean (diff) = 0	Degrees of freedom = 222	
Ha: mean (diff) < 0 p = 1,000	Ha: mean (diff) = 0 p = 0,000	Ha: mean (diff) > 0 p = 0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

10.5. Appendix E – Additional Analyses

E.1. Stated versus Actual Attention on Poster

As explained previously in section 5, there is often a difference to what subjects say they think or do and what they actually think or do. In literature, this is referred to as the stated preference bias, or hypothetical bias (Fifer et al., 2014). And with that, there might also be differences between peoples stated attention and revealed or actual attention.

The main research direction of this paper does not include these differences and no hypotheses are formed. However, it would be interesting though to test whether these differences exist. In the end, I used the eye tracking data to serve as a form of revealed attention, to overcome self-reported bias as explained before in section 5.1. In this section, I test for this to serve as a validation that only self-reported data might not be sufficient in marketing research, and as a researcher, you also need some form of revealed data.

E.1.1. Available Data

The available dataset offers plenty of opportunity to do test for these differences. I have self-reported data on attention, as I asked the subjects how much the poster captured the most attention. I also have revealed data, as the eye tracking reveals the attention the subjects actually had for the advertisement posters.

E.1.2. Procedure

First, I want to test whether there is a difference in the attention people said they had for the entire poster and the attention they actually had for the entire poster. As a measure for stated attention, I use the answers to the question "On a scale of 1 to 5, how much did the poster capture your attention?" (*AttentionStated*). As a measure for the actual action, I use *ViewingTime*, *GDTotal*, *NOFTotal* and *AFDTotal.*

However, in order to compare the two variables, they need to be on the same scale, and right now, the variables all have different scaling properties. The stated attention is on a 5-point Likert Scale, with a range from 1 to 5. All attention variables are on different scales, and the Attention Index score ranges from -6,177 to 7,586 (Table 8). To solve this problem, I decided to rescale all variables ranging from 0 to 4 and create an Attention Index Score on this scale as well.

For the stated attention, the answers were re-coded in the Excel data file where the lowest answer became 0 and the highest 4, instead of 1 and 5 respectively (now variable *AttentionStated4).*

For the actual attention, I rescaled the 4 above mentioned variables to be on the same scale (0 – 4) and took the average of those variables to generate the variable *AttentionIndex4.*

Now the two indicators of attention, both stated and actual (*AttentionStated4* and *AttentionIndex4),* are on the same scale which makes it possible to compare the two and test whether the means are significantly different.

Table 31: Descriptive Statistics Actual and Stated Attention

	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
AttentionStated4	223	1,888	2	0,964	0	4
AttentionIndex4	223	1,495	1,441	0,535	0,387	2,911

E.1.3. Results

Table 32: T-test Attention Actual and Stated

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
AttentionStated4	223	1,888	0,065	0,964	1,761	2,015
AttentionIndex4	223	1,495	0,036	0,535	1,425	1,566
Diff	223	0,393	0,071	1,063	0,252	0,533

diff = mean (AttentionStated4 – AttentionIndex4)		t = 5,516
H0: diff = 0		Degrees of freedom = 222
Ha: diff < 0 p = 1,000	Ha: diff = 0 p = 0,000	Ha: diff > 0 p = 0,000***

* = 10% significance level
** = 5% significance level
*** = 1% significance level

E.1.4. Interpretation

As can be seen in Table 32, the two variables have significantly different means, where the average stated attention is much higher (1,888) than the actual attention (1,495) (p-value = 0,000 < 0.01, significant at a 1% significance level). This is also what I expected based on the literature, as people tend to overstate or overestimate themselves (Quaife et al., 2018; Scott et al., 2016).

E.1.5 Conclusion

This finding proves the fact that there is a difference between stated attention and actual attention. IN section E.2, I also test the difference between stated and actual attention for different elements, and draw a general conclusion based on these two additional analyses.

E.2. Stated Versus Actual Attention per element

Since the previous section already proved that there was a difference between stated attention and actual attention for the entire poster, it raises the question whether this difference also exist when asking subjects what element captured their attention the most.

E.2.1. Expectations

In the experiment, I asked the subjects what element in the poster captured their attention the most, the picture or the text. Of the 223 observations[15], 110 times the subject said the text captured the most attention, and 113 times the subject chose the visual element, so approximately 50/50. However, in section 7.2, I have already shown that really, the textual element on average captured more attention than the picture. In this section, I will formally test the difference between stated and actual attention per element.

E.2.2. Procedure

In order to test the differences between stated and actual attention per element, all variables need to be on the same scale. As the stated attention is a binary variable that can take a value of 0 (= picture) and 1 (= text) (variable name is *AttentionStatedElement*, Table 4*)*, I need the attention index per element to be on the same scale. As to what variables are included in these Attention Scores, I go back to the section 7.2 where I explained what metrics are used to measure attention per AOI: gaze duration, number of fixations and average fixation duration. Obviously, viewing time (as this is included in the Attention Index Score for the entire poster) is a variable that cannot be used here, as this is about the stimulus as a whole and cannot be specified for separate AOI's.

I rescaled *NOFText*, *GDText* and *AFDText* to a 0 – 1 scale, and took the average of the 3 variables to create an Attention Score for the textual AOI. I did the same for the visual element, which provided me the following two variables:

$$AttentionText1_i = \frac{NOFText1_i + GDText1_i + AFDText1_i}{3}$$

$$AttentionPicture1_i = \frac{NOFPicture1_i + GDPicture1_i + AFDPicture1_i}{3}$$

Next, I created a variable that takes a value of 1 if the *AttentionText1* > *AttentionPicture1*, and 0 otherwise, meaning that when the value is 1, for that specific observation, the subject paid more attention to the textual element compared to the visual element, and if 0, the visual element captured the same or more attention than the textual (variable name is *AttentionActualElement)*.

[15] Note that I work with eye tracking data and therefore use the dataset that consists of 223 observations.

Table 33: Descriptive Statistics Actual and Stated Attention per element

	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
AttentionStatedElement	223	0,493	0	0,501	0	1
AttentionActualElement	223	0,547	1	0,499	0	1

To find out whether there are differences between the stated and actual attention per element, I perform do a t-test to compare the means and see whether these are significantly different.

E.2.3. Results

Table 34: T-test to test the difference between Attention Actual and Attention Stated per Element

N = 223	Observations	Mean	Standard Error	Standard Deviation	95 % Confidence Interval	
AttentionStatedElement	223	0,493	0,033	0,499	0,481	0,613
AttentionActualElement	223	0,547	0,034	0,501	0,427	0,559
Diff	223	-0,054	0,044	0,662	-0,141	0,336

diff = mean (AttentionStatedElement-AttentionActualElement)		t = -1,214
H0: diff = 0		Degrees of freedom = 222
Ha: diff < 0 p = 0,113	Ha: diff = 0 p = 0,226	Ha: diff > 0 p = 0,887

E.2.4. Interpretation

As can be seen, the p-value is approaching a 10% significance level (p = 0,113). It shows that subjects say that the picture captured slightly more attention, whereas in reality, the Attention Score was on average higher for the textual element compared to the visual element (as the mean is 0,547).

E.2.5. Conclusion

The results validate my expectations, that there are differences between what element captures the most attention and what element people think captured their attention the most. Of course, the differences are small and not (yet almost) significant, but it is still interesting to see that people do not always realize what actually captures their attention.

The outcome from this analysis, combined with the conclusion drawn in Appendix E.1, validates that in academic research, it is important to not only rely in self-reported data, because it is not always a true reflection of a person's intentions. Therefore, the use of eye-tracking technology was a valuable addition to this research.