The influence of protection and the effect of substance use on risk-taking behavior.

*Testing the Risk homeostasis theory and the effect of substance use on risk-taking behavior with a video game*
Abstract
The objective of the current study was to test the risk homeostasis theory in a controlled setting, since the theory has been somewhat controversial and it has been proposed that controlled laboratory experiments could help clear up the issue. Furthermore, this study also aimed to look at the moderating effect of substance use on risk homeostasis and the influence of substance use and substance use habits on risk-taking behavior, since the current established body of work regarding these effects raised questions that were not yet answered.

An experiment was conducted amongst 69 participants in a controlled setting using a video game as a tool to measure risk-taking behavior. Participants were tested on their risk-taking behavior, substance use (alcohol, cigarettes, marijuana, cocaine, ecstasy and amphetamine) and substance use habits (recency of use, frequency of use and quantity of use per time) for alcohol, cigarettes and marijuana. For recency of use, frequency of use and quantity of use participants who used a substance were divided into a low-, medium- and high recency of use, frequency of use and quantity of use group. This was done based on observations made on websites of online substance user communities and a study done by Van Der Pol and Van Laar (2015) regarding the amount of substances used in the Netherlands.

A homeostatic effect was found for more long-term risk compensation and not short-term risk compensation in general, which supported the risk homeostasis theory. Furthermore, users of cigarettes and marijuana both showed a similar amount of risk compensation as non-users, but cigarettes users started at a higher baseline. The comparisons of users of the other substances (i.e., alcohol, cocaine, ecstasy and amphetamine) did show interesting trends, but needed a larger sample size to check if these trends would persist.

The issue of small sample size also affected the results for the effect of substance use habits on risk-taking behavior. However, an interesting trend regarding quantity of alcohol used per time was found, and seemed to point at an increase of risk-taking behavior for participants who used larger amounts of alcohol per time.

In conclusion, the current study showed supporting evidence for the risk homeostasis theory, found new insights regarding the moderating effect of substance use on risk compensation strategies and yielded interesting trends regarding the effect of substance use habits on risk-taking behavior. These trends ask for further examination done with larger sample sizes than were used in this study, and, if possible, using a more reliable tool than a questionnaire to assess drug usage.
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1. Introduction

1.1 Risk-taking and the consequences

The famous racecar driver Mario Andretti once said “If everything seems under control, you’re not going fast enough.” (“Mario Andretti: A Glass Half Full for the Indy 500 and Formula One Champion”, 2009). He was known as quite a risky driver, and his attitude towards risk-taking might be more positive than that of others. However, risk-taking does seem to be part of the lives of all human beings and all of us take risks to some extent.

Most people think of risk-taking as something people only do consciously, but according to Fuller (as cited in Trimpop, 1994) and Trimpop (1994) it is important to also remember risk-taking that is not conscious. Fuller argued that the compensation process is not always conscious, especially when the risk-taking behavior is intrinsically rewarding (Fuller, 1984 as cited in Trimpop, 1994). Trimpop (1994) postulated that it is important to remember that risk taking should not be reduced to only conscious decision making. Another important issue brought up by Jungermann and Slovic (as cited in Trimpop, 1994) is that it is impossible to directly observe risk. Therefore, objective risk is an artificial construct reached by convention, such as expert judgments or calculations in hindsight of probability of outcomes (Trimpop, 1994). These objective risk estimates also do not account for the adaptations people make in their behavior to the perceived risks, which might differ greatly from the aforementioned objective risks. Since perceived risks are what people base their risk-taking decisions on, this study will focus on perceived risks.

There is an inherent problem with both conscious risk-taking behavior and unconscious risk-taking behavior; it can lead to terrible accidents in all sorts of situations and occupations. These accidents include the deaths of racecar drivers during their race when they take a risky turn to pass another driver, or the deaths of industrial workers when they try to do a procedure in a way that saves time, but ultimately can lead to chemical leaks, explosions or other dangerous outcomes. Human error, or unsafe behavior, in traffic alone has been found to be a major cause of accidents (Lu, 2006). This unsafe behavior can partially be attributed to risk-taking (Reason, Manstead, Stradling, Baxter & Cambell, 1990; Reason, 2000). Traffic is but one of the areas where the risk-taking behavior of people leads to accidents, and there are many more areas where this behavior can lead to dangerous or costly outcomes. Research done within the EU-28 in 2012 by Eurostat, the statistical office of the European Union, found that almost 2.5 million non-fatal accidents that resulted in a minimum of four calendar days of absence occurred and another 3515 fatal accidents occurred. This was 1702 non-fatal accidents and 2.44 fatal accidents per hundred-thousand
persons employed (“Accidents at work statistics”, 2015). The International Labour Organization (ILO) also reported that globally 317 million accidents occur on the job every year that often lead to extended absences from work and it also reported a total of 2.3 million deaths every year due to occupational accidents. They estimated that poor occupational safety and health practices cost a total of 4% of the global Gross Domestic Product each year (“Safety and health at work”, 2016). These enormous amounts of accidents have lead to issues ranging from loss of productive time at work to loss of life.

This leads one to wonder how much of these accidents are caused by our own mistakes. In a study done by Hale and Glendon (1987) it was found that around 80% of accidents are accounted for by human error (unsafe behavior), at the individual or organizational level, and only around 20% is accounted for by technical components. Another study done in Finland even found that human errors were involved in 84% of serious occupational accidents and 94% of fatal occupational accidents (Salminen & Tallberg, 1996). Findings like these and others, such as the finding that approximately 70% of aircraft accidents were caused by human error (Feggetter, 1982), have led to the understanding that most accidents have human error components to them. In most cases accidents are at least partially caused by our own unsafe behavior, or errors.

But how many of these errors are due to people engaging in risk-taking behavior? Wagenaar, Hudson and Reason (1990) argued that many unsafe acts are not due to slips or simple errors, but often intentional and reasoned actions that end in unforeseen results. They found not many occupational accidents occur due to workers trying to experience an adrenaline thrill or be in a flow-experience. The idea that accidents are caused by reasoned actions that end in unforeseen results (risk-taking behavior) is also supported by a more recent Mexican study in the manufacturing industry (Reyes-Martinez, Maldonado-Macias & Prado-León, 2012). It was found that the most frequent human errors that caused accidents leading to hand injuries were improper handling of heavy objects, attempts to save time in conducting operations and the operator not respecting the rules and safety procedures. The latter two of these three causes are both in line with the findings and ideas of Wagenaar and his colleagues (1990). A large part of human error seems to be due to risk-taking behavior.

This leads us to an important question: Why do people take the risks that they take? The first reason would be intrinsic motivations for risk-taking behavior. In 1895 Freud and Breuer (as cited in Trimpop, 1994) already assumed that organisms tried to maintain a constant intracerebral excitement level. Since there are individual differences in the nervous system of people, they said that it is possible they have different optimal levels of arousal.
Later theories and research regarding optimal arousal levels showed support for the idea of optimal levels of arousal (Berlyne, 1960; 1971; Hebb, 1949; 1955; Yerkes & Dodson, 1908 as all cited in Trimpop, 1994; Thayer, 1967; 1972; 1978; 1987). Yerkes and Dodson (as cited in Trimpop, 1994) found that performance on complex tasks was related to arousal with a curve in the shape of an inverted-U and performance on simple tasks was linearly related to increased arousal. It would therefore make sense that individuals would have a need to tune their arousal to an optimal level depending on the situation. Other researchers stated that there was an inherent pleasure from taking risks (Hebb, 1949 as cited in Trimpop, 1994) due to changes in arousal and that it helped avoid boredom when increasing arousal (Berlyne as cited in Trimpop, 1994) when it was too low. All of these theories and findings on arousal support that people would try to maintain a relatively stable level of perceived risk suited to specific situations, since they would want to maintain their optimal level of arousal. This supports the idea that there would also be an optimal level of perceived risk. People would be intrinsically motivated to try and maintain this perceived risk level. The other reason is extrinsic motivation. There could be factors making the risk that is taken worth it, since they are more important than safety. This could also be dictated by the culture at a workplace (Cox & Cox, 1991). Regarding the workplace it has been found that there are some cases of workers engaging in dangerous activities to show off or where they are proud to use their improvisation skills (Trimpop, 1993 as cited in Trimpop, 1994), but most risk-taking behavior causing occupational accidents seems to be caused by workers having more important priorities. These priorities are things like finishing the job on time, avoiding time loss by using improvised tools, keeping the engines running, making more profit, et cetera (Apter, 1984). In part of cases this has to do with the safety culture and climate at a workplace (Cox & Cox, 1991). This is made up of the shared attitudes, beliefs, perceptions and values among employees regarding safety. If, for example, the culture dictates productivity is more important than safety, people will more easily disregard safety if productivity might suffer if they followed procedures.

When looking at the large amount of accidents occurring, the enormous amount of loss of productivity and loss of life, it becomes clear that prevention of these accidents is of paramount importance. It would lead to the saving of millions of lives over the years, prevention of millions of injuries, and prevention of damage to the environment. It would also lead to a large decrease of loss of resources due to accidents (e.g., less road repair, less vehicle repair, less time lost due to delays caused by accidents, less loss of products or materials, less medical costs due to injuries, less loss of work time due to injuries).
Therefore, it is important to determine what factors influence the decision of people to engage in risk-taking behavior. There is a large body of research on this topic, part of which we looked at earlier. However, it is important to keep expanding our knowledge of the reasons underlying the risks people take, since this knowledge can be used to develop strategies, plans and interventions to decrease risk-taking behavior in places where it is important to do so. Examples would be the construction industry, the manufacturing industry, the aviation industry, and the chemical industry, among others. This in turn will help reduce the amount of (fatal) accidents, injuries, damage to the environment and loss of resources.

1.2 Risk homeostasis theory

The large body of research on risk-taking includes a large variety of theories regarding the factors influencing risk-taking behavior. Some important ones will be briefly discussed before the choice of studying the risk homeostasis theory (Wilde, 1982) will be explained.

First off there are the aforementioned theories on arousal and risk-taking behavior (Berlyne, 1960; 1971; Freud & Breuer, 1895; Hebb, 1949; 1955; Yerkes & Dodson, 1908 as all cited in Trimpop, 1994; Thayer, 1967; 1972; 1978; 1987), which theorize performance can be improved through maintaining an optimal level of arousal and that taking risks can be pleasurable and help avoid boredom through an increase of arousal levels. This group of theories focuses on intrinsic motivations for risk-taking behavior. Another group of theories concerns individual differences, mostly in personality traits. Theories like Eysenck’s personality theory (Eysenck, 1947 as cited in Trimpop, 1994) grouped habits of people into personality dimensions and started comparing the differences between people who were on the opposite end of the same personality dimension, such as introvert personalities versus extravert personalities. People scoring higher on the extraversion scale and the psychoticism scale would be people who take more risks, since extraversion relates to being interested in new and novel experiences and psychoticism relates to anti-social behavior and that is considered risk-taking behavior (Zuckerman, 1979). Another related theory is Zuckerman’s optimal level of arousal theory (Zuckerman, 1979), which lead to the development of the well-known sensation seeking scale (Zuckerman, Kolin, Price & Zoob, 1964 as cited in Trimpop, 1994). Sensation seeking was linked to risk taking in further research, as expected (Zuckerman, 1979). This group of theories also focuses on intrinsic motivations for risk-taking behavior. Yet another group of theories sees risk taking as the making of decisions under uncertainty and assumes that people always make rational choices to maximize their
profit, while tolerating risks as unwanted by-products of uncertainty (Trimpop, 1994). This group of theories focuses on extrinsic motivations for risk-taking behavior and disregards intrinsic motivations to display risk-taking behavior. Closely related are utility theories, with a big difference being that they also account for intrinsic motivations, such as how much a loss is actually feared and how much people want to protect their self-image (Josephs, Larrick, Steele & Nisbett, 1993) or would enjoy increased arousal (Fischhoff, Furby & Gregory, 1987). This group of theories still maintains that people will rationally decide to take risks or not. However, Trimpop (1994) argues that emotions are motivators for risk-taking behavior just as much as rational thought is. Furthermore, other studies have also shown a direct link between positive emotions and increased risk-taking behavior (Johnson & Tversky, 1983; Isen & Patrick, 1983).

This study will look at an explanation of risk-taking behavior that has not yet been explored much outside of a traffic context. This is the risk homeostasis theory (Wilde, 1982). Wilde (1982) theorizes, among other things, that preventive interventions, or protective measures, might lead people to perceive their risk level to be lower and they will thus try to engage in more risky behavior if they perceive that there are rewards to be gained (Wilde, Robertson & Pless, 2002), such as saved time, saved effort, higher productivity, and saved mental energy, among others. It is an interesting theory, since it puts a lot of focus on what people actually perceive, and as was said before, people base their decisions on what they perceive. The theory also acknowledges something important which a lot of theories do not; the fact that people might want to adjust their risk-taking behavior in a certain way, but might not possess the skills needed to adjust their behavior in the way they want. Another reason why it is an important theory to look into is the combination of all possible costs and benefits being weighed. This means it does not limit itself to only emotional, rational, intrinsic motivational or extrinsic motivational factors, but combines them. Furthermore the theory has a very important implication. People are usually aware of the protective measures around them. This theory implies that this awareness might actually be a bad thing, since people might perceive their level of risk to be lower and start showing more risk-taking behavior for the potential benefits they perceive. This would undermine the effectiveness of any safety measures. If this theory can be supported outside of a traffic context, it could mean that in these other contexts it will be important to influence the target level of risk of people through measures such as rewarding safe behavior and punishing unsafe behavior. This could have a large impact on the safety measures within a lot of contexts. It is therefore important to test the theory outside of a traffic context.
The risk homeostasis theory was originally designed to serve as an explanatory framework for the causes of car traffic accidents (Wilde, 1982) and has mostly been researched in car traffic settings (Aschenbrenner & Biehl, 1994; Grant & Smiley, 1993; Jackson & Blackman, 1994; Wilde, 1998; Wilde et al., 2002). The theory states that there are two different levels of risk: the perceived risk level and the target risk level. Wilde (1982) states that an individual will not try to minimize the risk level in a situation, but instead optimize it to reach their target level of risk. This means that at any point of time an individual compares the level of perceived risk with their target level of risk and will change their behavior to try to eliminate the difference between the two. By changing their actions to reduce this perceived difference, they change the amount of accidents that happen. This in turn over time changes the perceived risk through lagged feedback and influences the decision again (Figure 1).

Figure 1. Risk homeostatic model on driving behavior (Wilde, 1982).

According to Wilde (1982) people base their target level of risk on an analysis of the costs and benefits. This analysis is made up of four factors:
1. The expected benefits of risk-taking behavior.
2. The expected costs of risk-taking behavior.
3. The expected benefits of safe behavior.
4. The expected costs of safe behavior.
When the weighed utility of showing more risk-taking behavior is higher than the weighed utility of showing safe behavior, someone is expected to show more risk-taking behavior.
However, if the weighed utility of showing more risk-taking behavior is lower than the weighted utility of showing safer behavior, someone is expected to show less risk-taking behavior. As the factors determining the expected benefits and costs change, partially due to someone’s own actions, so does the outcome of the new analysis and the target risk level.

The perceived level of risk, according to Wilde (1982) is based on the perceptual skills of the person, which vary from person to person. The other determinant is feedback coming from accident rates. As accident rates are not immediately available, old information might be used for some time (lagged feedback).

Once someone has determined their target level of risk and their perceived level of risk, they compare the two and try to determine their desired adjustment. This desired adjustment is based on trying to bring the perceived level of risk as close as possible to the target level of risk (Wilde, 1982).

The adjustment behavior people will actually show in traffic settings is influenced by three factors: (1) someone’s desired adjustment in behavior, (2) someone’s decision making skills and (3) someone’s vehicle handling skills (Wilde, 1982).

Wilde (1982) compares the risk homeostasis effect to how a thermostat works. A thermostat is always set to try to change the temperature in an area to a target level, which is similar to the target level of risk. The temperature in the room can be hotter or colder than this target level. This is the perceived temperature, which is similar to the perceived risk level. A thermostat is designed to start heating or cooling a room based on the difference between the perceived temperature and the target temperature to try and reach the target temperature. This is similar to the desired adjustment people decide on based on the difference between the perceived risk level and the target risk level. However, the adjustment the thermostat makes is also dependent on factors such as the capacity of the heater the thermostat controls. The adjustment the thermostat makes might not be the same as the desired adjustment. This is similar to how the eventual adjustment action might not be the same as the desired adjustment for people, as the adjustment action is also dependent on their decision making skills and vehicle handling skills. The target temperature depends on what the person setting the thermostat wants and what the context is. This is similar to the target risk level. A thermostat is also regularly checking the perceived temperature, just as a person regularly checks the perceived risk level. In both cases the actions are adjusted to the new perceived temperature or perceived risk level. Since a room does not heat up or cool down instantly and the amount of accidents a person is aware of does not change instantly, the phenomenon of lagged feedback plays a role in both cases.
The assumption of Wilde (1989) is that to lower the amount of accidents the only solution is to lower the target level of risk people have. The most promising solution to lower people’s target level of risk, according to Wilde, Robertson and Pless (2002), was to reward safe driving behavior and punish risk-taking behavior.

1.2.1 Risk homeostasis theory: conflicting findings
The risk homeostasis theory has been studied in many different studies with different settings, and the evidence that can be found is quite conflicting. A summation of the evidence supporting the risk homeostasis theory, the evidence refuting the risk homeostasis theory and criticism regarding the risk homeostasis theory will be discussed in this section.

Several real-life studies have shown supporting evidence for the risk homeostasis theory. In 1968 Sweden changed from driving on the left-hand side of the road to driving on the right-hand side of the road. Shortly after the introduction of these new traffic rules the accident rates went down. Two years later the accident rates returned to normal. Wilde (Wilde, 1998; Wilde et al., 2002) assumed that the change initially increased the perceived level of risk of Swedish road users. Due to this they compensated by showing less risk-taking behavior when driving. Once the drivers were used to driving on the right-hand side of the road, the perceived level of risk decreased again. Drivers then compensated by showing more risk-taking behavior and the accident rates returned to what they were before.

Another real-life study supporting the theory comes from Grant and Smiley (1993). They found that taxi drivers in Canada who got a cab equipped with anti-lock brakes (ABS), which they previously did not have, started showing more risk-taking behavior. This led to the same accident rates over time, even though the cabs themselves had added safety measures. Aschenbrenner and Biehl (1994) found similar results a year later in a comparable study done amongst taxi drivers in Munich.

Other studies showing supporting evidence for the risk homeostasis theory have been done using driving simulations. In one of such studies Jackson and Blackman (1994) found that increasing the costs of risk-taking behavior resulted in a reduction of the amount of accidents. Similar results were found in another driving simulator test. Fewer accidents occurred in an environment where the perceived level of risk was high as compared to an environment where the perceived level of risk was low (Hoyes, Stanton & Taylor, 1996).

Another study found support for the risk homeostasis theory, but concluded that risk compensation could occur in a shorter time (Glendon, Hoyes, Haigney & Taylor, 1996). This evidence contradicts the risk homeostasis theory, as the theory states that risk compensation
can take months or years (Wilde, 1989). The authors indicated that this may have had to do with the more immediate feedback in the simulation as compared to real-life traffic settings (Glendon et al., 1996).

Although the risk homeostasis theory was originally created for car traffic, support for the theory has also been found in other domains. Baniela and Rios (2010) found that within the maritime industry continuous advances in the safety of navigation did not reduce the occurrence of shipping casualties. They found evidence that the perceived benefits of risk-taking behavior compared to safer behavior (higher pay if the journey took less time), when combined with the lower perceived risk due to more safety measures, led captains to be willing to take more risks when they were given more safety measures. This in turn led to a similar risk level, which led to the lack of reduction of shipping casualties according to Baniela and Rios (2010). This was consistent with the risk homeostasis theory. Another study found support for the risk homeostasis theory in the domain of computer use (Sawyer, Kernan, Conlon & Garland, 1999). They examined computer use after the threat of the Michelangelo computer virus. They found that the strength of the experience of risk led to performing more protective behaviors. They also found that although the evaluation of the population risk people made went up, they evaluated their personal risk level to be similar. This indicated that people performed the extra protective behaviors when their perceived risk went up. This made their personal perceived risk go back down to the levels they were before the threat of the computer virus was there (Sawyer et al., 1999). This was consistent with the risk homeostasis theory.

Most scientific theories have their critics, and this goes for the risk homeostasis theory as well. Evans (1986) did a very thorough study on existing traffic data and came to the conclusion that it did not support the risk homeostasis theory. He states that the amount of fatalities was not stable in any of the traffic accident data, and even indicated that the original evidence supporting the risk homeostasis theory suffered from methodological shortcomings and, if anything, was evidence to refute the risk homeostasis theory.

More criticism came from Stetzer and Hofmann (1996), whom believed that the risk homeostasis theory should mostly be tested on an individual level. They argued that many studies either use aggregate data and are thus inappropriately crossing levels (i.e., using general data to test an individual theory), or fail to measure key variables (i.e., subjective risk, target risk level). In their study they tried to measure risk compensation at an individual level and measured the key variables. They found that people showed risk compensation, but did not compensate for changes in the environment enough to return to their original level of
risk. They concluded that the evidence was not strong enough to support the risk homeostasis theory (Stetzer & Hofmann, 1996).

Additional criticism has come from several researchers, who have questioned whether the risk homeostasis theory can be falsified (Adams, 1988; Glendon et al., 1996; Hoyes & Glendon, 1993). Adams (1988) was of the opinion that even though the risk homeostasis theory sounded plausible, it was not testable. He described the theory as a metaphysical concept that accounted for behavior which nobody had yet succeeded in connecting to real-life settings and measuring with an accepted tool. Hoyes and Glendon (1993) added that the risk homeostasis theory was impossible to falsify in a real traffic setting. They stated that the theory does not explain how individuals determine their target risk level, and also does not mention how the target risk level can be measured. This led them to the following question: If the only way to change accident rates is to change the target level of risk, how do we tell the target level of risk has changed? They argued it is circular to just look at accident statistics for this reason, since any change in the amount of accidents would only lead to the conclusion that the target level of risk must have changed. Even if the amount of accidents stayed the same, this would only lead to the conclusion that the target level of risk must have stayed the same. The theory would always be correct, and thus not falsifiable. Glendon et al. (1996) were also of the opinion that the risk homeostasis theory could not be tested in a real-life setting, since it is impossible to control all the pathways through which homeostasis might happen. However, they did argue that it might be possible that a well-designed experiment in a laboratory could control the important factors that influence risk homeostasis and would be able to falsify the theory. Their first requirement was that there should be a good reason to suppose participants are characterized by a target level of risk and they warned that a reduced attention level, for example through boredom, disturbs the target level of risk. Their second requirement was that errors needed to be within the control of participants. They should not be doing so due to constraints of the environment or rules. Their third requirement, based on comments of participants, was that manipulations of environmental safety needed to be relevant to the probability of an accident instead of the costs of an accident (Glendon et al., 1996).

1.3 Risk-taking and substance use
Another area of study that has had the interest of many researchers has been substance use and the relation it has to risk-taking behavior. The use of substances such as drinking alcohol, smoking cigarettes and use of illegal substances (e.g., cocaine, ecstasy,
amphetamine) can be seen as risky, since they carry risks to the health of users (i.e., negative effects on the body and higher possibility of accidents when under influence). On top of that, the illegal substances carry the extra risks associated with being illegal. Using such substances can get users in trouble with the authorities and the quality control on such substances is often less strict, since the government does not have as much influence in the quality control. This leads to an increased potential risk of getting punished by the authorities (e.g., getting fined, having to spend time in prison, being forced to go into rehab), illness or even death when using illegal substances (due to the risk of wrong doses and dangerous chemicals being in the substances being higher). It is thus often expected that substance use would be linked to risk-taking behavior. This relation is usually expected to be positive; people expect that substance users will show more risky behavior.

Thus far the body of research in real-life settings suggests that this expectation seems correct. Two studies (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999) looked into the alcohol consumption of patients in the emergency room (ER). Cherpitel found that the amount of problem drinkers, the frequency of alcohol consumption and quantity of alcohol consumption were higher among those seeking ER treatments for injuries as compared to the general population that they came from. Since injuries can be partially explained by people engaging in more risk-taking behavior, this pointed towards this group showing more risk-taking behavior.

Another study done by Tapert, Aarons, Sedlar and Brown (2001) compared the sexual behaviors of adolescents with a history of substance use disorders with youths without such histories. They found that the adolescents with a history of substance use disorders showed more signs of risky sexual behavior. They had an earlier age of onset sexual activity, had had more sexual partners, used condoms less consistently and had more sexually transmitted diseases.

Several other studies have also showed evidence supporting that the use of illegal substances is associated with high levels of impulsivity and propensity to engage in more risk-taking behavior. These behaviors included exchanging sex for drugs or money, criminal activities (e.g., property offenses, violent crimes) and sharing of drug paraphernalia (Centers for Disease Control and Prevention, 1999; Chitwood et al., 2000; Friedman, 1998; Joe & Simpson, 1995; Kral, Bluthenthal, Booth, & Watters, 1998; Murray et al., 2003; Rhodes et al., 1990).

Besides the associations found in studies done in real-life settings, associations between risk-taking and substance use have also been found using experiments in laboratory
settings. Importantly, studies that support the assumptions that were made based on the findings in the studies done by Cherpitel (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999) have been found. These studies supporting the aforementioned assumptions were two studies that were also about alcohol consumption. The researchers in these studies found that the frequency of alcohol consumption and the quantity of alcohol consumption were both related to risk-taking (Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011). Higher frequency of consumption of alcohol and higher quantity of consumption of alcohol were both related to higher levels of risk-taking.

For several other substances differences in risk-taking behavior between users and non-users were found. Lejuez et al. (2003) assessed risk-taking behaviors using the balloon analogue risk task (BART; Lejuez et al., 2002) and found that users of cigarettes showed more risk-taking behavior than non-users. Similar results using the balloon analogue risk task (BART; Lejuez et al., 2002) were found when comparing adolescent marijuana users to adolescent non-users (Hanson, Thayer & Tapert, 2014). Two other studies compared stimulant users to non-users using different kinds of tasks (Hopko et al., 2006; Leland & Paulus, 2005). The researchers in these studies also found an increase of risk-taking behavior of users as compared to non-users.

The research regarding the relation of frequency of consumption of alcohol and quantity of consumption of alcohol to risk-taking behavior found in the aforementioned studies (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011) led to the question if similar relations could be found for other substances and whether recency of use would possibly show a similar relation to risk-taking behavior. Furthermore, the body of evidence regarding substance use shows strong support for the positive relation between risk-taking behavior and use of any of several different substances. This led to the question whether different risk compensation strategies would be prevalent amongst different substance user groups as compared to non-users. Based on the risk homeostasis model it was theorized that differences might exist between the target risk levels of substance users as compared to non-users. Another option was that differences existed between the perceived risk levels of substance users as compared to non-users. Any of these differences were expected to be present without the consumption of any substances during this study, since the differences were expected to be hard-wired within people. These expectations were based on the aforementioned research regarding substance use showing differences between users and non-users, even when no substances were used during the study (Centers for Disease Control
and Prevention, 1999; Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Chitwood et al., 2000; Friedman, 1998; Hanson et al., 2014; Joe & Simpson, 1995; Kral, Bluthenthal, Booth, & Watters, 1998; Lejuez et al., 2002; Murray et al., 2003; Rhodes et al., 1990). The first step seemed to be to determine whether different risk homeostatic effects could be observed in substance users and non-users. If this turned out to be the case, more research could be done into which factors of the model caused the difference. This could be (1) someone’s desired adjustment in behavior, (2) someone’s decision making skills and (3) someone’s skills to perform the task at hand (Wilde, 1982). As mentioned, the assumption was made that differences between users and non-users would be caused by differences in target level of risk and perceived level of risk. These two factors make up someone’s desired adjustment in behavior in the model. However, if any differences were found, it would be necessary to also look into the possibility of differences in decision making skills and skills at performing the task at hand.

1.4 Current study

The goal of the current study is to try and test the risk homeostasis theory using a video game in a laboratory setting. Since the theory has been said to be falsifiable in a properly designed laboratory setting, this study will help gain more insight into risk-taking behavior and the effects of objectively different protective measures on this behavior. To achieve this attention needs to be paid to the aforementioned requirements (Glendon et al., 1996). First off, it is important that the game communicates clearly how well protected someone is and it needs to keep the attention of participants. It is also important to randomize the order of safer and less safe rounds. That way if something like reduced attention through boredom creeps in at certain parts of the testing, such as the beginning, the middle or the end, the effect of it on the data will averagely be largely cancelled out due to each round averagely having equal amounts of boredom involved. As such, the differences between rounds on average are expected to remain similar. Second, it is important to make sure the only way errors can be made in the game is if the participants themselves make these errors freely and not due to constraints or rules. The game will give full control to the participant to make their own errors. The third requirement was based on comments of participants, and not data analysis. On top of that this study is interested in the effect of the amount of perceived risk with protective measures in place. Therefore, this requirement will not be taken into account in this study. The manipulation will be done using different amounts of lives or shields in different rounds and displaying the amount of shields left to participants at all times. These
shields arguably represent the costs of an accident and not the probability of an accident. This is done since they also very simply represent the protective measures many workplaces might have and the fact that workers are aware of these measures.

Besides the scientific relevance of testing the risk homeostasis theory, evidence supporting the theory, and thus indicating negative effects of protective measures, could also influence society. Companies and government institutions would have to start considering the effects of their communication about the use of safety measures. Studies about risk communication have already been done and could be used to improve said communication. In their research about injury prevention and risk communication Austin and Fischhoff (2012) stated that mental models can lead people to make poor choices, because actions feel so natural that they are taken without thinking, people underestimate risks, people overestimate the effectiveness of protective measures, people cannot understand instructions well enough to follow them, or people do not recognize changes in their circumstances that affect risk. They argue that it is important for institutions to first make a formal model of the risk situation based on domain expert beliefs. They should then take a look at the beliefs of the relative laymen about the same domain. A comparison will need to be made to identify gaps and misperceptions between the two. Next, structured surveys should be used to estimate how prevalent the beliefs of the laymen are amongst the population of interest to the institution. After following these steps the information that is obtained can be used to develop and evaluate the right communications (Austin & Fischhoff, 2012). In another study about communicating about the risks of terrorism Fischhoff (2011) said that several human tendencies explain why officials sometimes rely on intuition instead of research, even when research is inexpensive compared to the stakes riding on successful communication. These tendencies were exaggerating how well one communicates, unknowingly lacking empathy for others’ circumstances and information needs, misreading earlier events and underestimating people’s ability to learn and make decisions. Fischhoff (2011) made a case for the importance of effective communication and having the right staff within an institution to do so. He argued for the need of psychologists to study the needs of their audience and to design and evaluate communications. Furthermore subject-matter experts would be needed to ensure the accuracy of the messages being sent. Risk and decision analysts would have to identify the most critical facts from the information of these subject-matter experts. Communication specialists would also be needed to create channels to stay in touch. Finally institutions would need leaders who could coordinate this group of diverse professionals and keep them focused on their own areas of expertise (Fischhoff, 2011). Although this study
was focused on larger societal risks, the ideas within it are also relevant for communicating risks in any company or institute. Better communication about protective measures and risks in general might prove necessary if the risk homeostasis theory grows more support outside of a traffic context. The current study could be a start of that growing support.

The risk homeostasis theory is a decently supported theory, and thus the expectation is that objectively larger protective measures (independent variable) in the video game will lead to larger levels of risk-taking behavior (dependent variable) by participants. Participants will do this to adjust to the larger perceived gaps between their perceived risk level and target risk level. This would indicate compensating behavior as described in the risk homeostasis theory (Wilde, 1982).

It is important to clearly define risk compensation and risk homeostasis. Risk compensation can be defined as changing behavior based on a difference between the desired level of risk and the perceived level of risk. Risk homeostasis, as defined by Wilde (1982), refers to the optimizing of the level of taken risk in a homeostatic way. This means that the observed level of risk is always trying to be matched with the target level of risk by people. It is important to mention that Wilde (1988) distinguished homeostasis from isostasis, which is an invariable, constant level of risk. Homeostasis is often mistaken for isostasis, but Wilde (1982) originally spoke of a fluctuating level of risk, which only averagely matches a certain target level of risk. Risk homeostasis does however still imply compensation all the way back to a previous target risk level after a change in the perceived risk level. In contrast, Janssen and Tenkink (1988) argued that in most situations only partial compensation took place for safety measures and so did Stetzer and Hofmann (1996). However, they did not consider that the risk-taking behavior might move to other activities or other times. Trimpop (1994) says that up to date no study had been published yet that controlled for many or all possible shifts in risk-taking behavior. A partial compensation can still be seen as a homeostatic process, but it is different from the optimized compensation expected when we think of risk homeostasis. In the case of partial compensation, it could be possible other factors besides the homeostatic process also play a role. In the current study risk compensation will be seen as support for the risk homeostasis theory, since Wilde (1982) argues that over time the system will maintain a homeostatic risk level, but the risk level fluctuates to compensate for environmental changes. If participants only show partial compensation, this can be explained by said fluctuations. Therefore, as long as risk-taking behavior increases with objectively larger protective measures, it will support the idea of a homeostatic process and thus the risk homeostasis theory by Wilde (1982).
Besides testing the risk homeostasis theory, the study will examine the effect of substance use (users versus non-users), recency of substance use, frequency of substance use and quantity of substance use per time on risk-taking behavior. Which substances will be examined has been based on legal substances that are used on a large scale within the Netherlands (i.e., alcohol and cigarettes) and research into the amount of use of other (mostly illegal) substances (Van der Pol & Van Laar, 2015). The most used substances found in this research were marijuana, cocaine, ecstasy, and amphetamine and thus these substances were deemed interesting to include. However, the expectation was that groups of users would be too small for the users of cocaine, ecstasy and amphetamine, and thus this study will only compare users to non-users for these substances. Therefore the substances being examined in this study were split the following way: (1) alcohol, cigarettes, and marijuana (looking at users versus non-users, recency of use, frequency of use and quantity of use within the user group) and (2) cocaine, ecstasy and amphetamine (only comparing users to non-users). The expectations are that users of any of the substances will show more risk-taking behavior compared to non-users. Similarly, it is expected that for the chosen substances (alcohol, cigarettes, and marijuana) the more recent use, more frequent use and higher quantity of use per time will all lead to more risk-taking behavior. For recency of use, frequency of use and quantity of use participants were divided into three groups: low, medium and high recency-, frequency- and quantity of use. The cutoff points for each of these three groups were based on observations made on websites of online substance user communities and the study done by Van Der Pol and Van Laar (2015) regarding the amount of drugs used in the Netherlands.

Finally; this study will examine the moderating effect on risk homeostasis of being a user of different substances (users versus non-users) for the same substances (alcohol, cigarettes, marijuana, cocaine, ecstasy and amphetamine). Earlier research has linked alcohol use (Schwarz, Burkhart & Green, 1978), use of illegal drugs (Kohn & Coulas, 1985) and smoking (Zuckerman & Neeb, 1980) to higher sensation seeking. Higher sensation seeking has been linked to the desire to seek out of more risk and to more risk-taking behavior (Zuckerman, 1979). Combining the findings from these studies leads to the understanding that users of alcohol, cigarettes, marijuana, cocaine, ecstasy and amphetamine are likely all more sensation seeking than non-users. The craving for more risk in sensation seekers can easily be linked to the first factor influencing the adjustment behavior of people in the model of Wilde (1982); someone’s desired adjustment behavior. This author theorizes that the expected difference in desired adjustment behavior would be due to a higher target risk level.
amongst the more sensation seeking users as compared to non-users, since sensation seeking is linked to seeking out risk. However, it is possible that users simply have lower perceived risk levels in the same situation as compared to non-users. Due to the expected differences between users and non-users in desired adjustment behavior, the expectation is that users and non-users of the substances (alcohol, cigarettes, marijuana, cocaine, ecstasy and amphetamine) will have different risk compensation strategies.

The three main questions of this study are: (1) What is the effect of being aware of protective measures on risk-taking behavior, and what is the moderating effect of substance use? and (2) Do users of the researched substances show more risk-taking than non-users? and (3) Do more recent use-, more frequent use- and higher quantity of use per time of the researched substances lead to more risk-taking?

This has led to the forming of the following hypotheses:

*Hypothesis 1.* Being aware of higher levels of protection is related to more risk-taking behavior.

*Hypothesis 2A.* Users of alcohol show more risk-taking behavior than non-users.

*Hypothesis 2B.* Usage of alcohol influences the risk-compensation strategy.

*Hypothesis 2C.* More recent use of alcohol is related to higher risk-taking behavior.

*Hypothesis 2D.* More frequent use of alcohol is related to higher risk-taking behavior.

*Hypothesis 2E.* Usage of higher quantities of alcohol per time is related to higher risk-taking behavior.

*Hypothesis 3A.* Users of cigarettes show more risk-taking behavior than non-users.

*Hypothesis 3B.* Usage of cigarettes influences the risk-compensation strategy.

*Hypothesis 3c.* More recent use of cigarettes is related to higher risk-taking behavior.

*Hypothesis 3D.* More frequent use of cigarettes is related to higher risk-taking behavior.

*Hypothesis 3E.* Usage of higher quantities of cigarettes per time is related to higher risk-taking behavior.

*Hypothesis 4A.* Users of marijuana show more risk-taking behavior than non-users.

*Hypothesis 4B.* Usage of marijuana influences the risk-compensation strategy.

*Hypothesis 4C.* More recent use of marijuana is related to higher risk-taking behavior.

*Hypothesis 4D.* More frequent use of marijuana is related to higher risk-taking behavior.
Hypothesis 4E. Usage of higher quantities of marijuana per time is related to higher risk-taking behavior.

Hypothesis 5A. Users of cocaine show more risk-taking behavior than non-users.
Hypothesis 5B. Usage of cocaine influences the risk-compensation strategy.

Hypothesis 6A. Users of ecstasy show more risk-taking behavior than non-users.
Hypothesis 6B. Usage of ecstasy influences the risk-compensation strategy.

Hypothesis 7A. Users of amphetamine show more risk-taking behavior than non-users.
Hypothesis 7B. Usage of amphetamine influences the risk-compensation strategy.

To illustrate the hypotheses several figures were added (Figure 2, Figure 3 and Figure 4).

Figure 2. Schematic representation of hypothesis 1.

Figure 3. Schematic representation of hypothesis 2A, 2C, 2D, 2E, 3A, 3c, 3D, 3E, 4A, 4C, 4D, 4E, 5A, 6A, and 7A.

Figure 4. Schematic representation of hypothesis 2B, 3B, 4B, 5B, 6B, and 7B.
2. Methods

2.1 Participants
Most of the participants were recruited using the research participation program of Leiden University (62 subscribed, of which 51 participated). The remaining participants were recruited by looking for participants within the social network of the research team, using flyers at the faculty of social sciences of Leiden University, and verbally persuading people within the premises of the faculty of social sciences of Leiden University to participate.

Once recruitment was done, a total of 69 participants were recruited for participation in this study. The sample of participants was mostly female; 58 females, and 11 males. The age of the participants ranged from 18 to 36 years (\(M = 22.41, SD = 3.22\)). The highest completed education amongst participants ranged from HAVO, which stands for Hoger Algemeen Voorbereidend Onderwijs (Dutch secondary educational system, literally “higher general continued education”) to a Master degree in university. The majority completed either VWO (N = 33), which stands for Voorbereidend Wetenschappelijk Onderwijs (Dutch secondary educational system, literally “preparatory scientific education”), or a Bachelor degree in university (N = 23).

The exclusion criteria for this study were the presence of at least one neurological condition (e.g. epilepsy, narcolepsy, essential tremor, multiple sclerosis, and Tourette’s syndrome), or experience in the past with the game used in the experiment. No technical issues or data processing issues occurred during the study. This resulted in a complete sample of data for all participants.

2.2 Materials
Two different materials were used to gather data; a self-developed questionnaire and a video game (the Spaceship game).

2.2.1 Self-developed questionnaire
A questionnaire was used to gather the information about the substance use of the participants. The entire questionnaire was filled out by participants using the computer. The part of the questionnaire that was relevant to this study consisted of one general question, three demographic questions and several questions regarding the substance use of participants (see Appendix A). The first of the questions on each substance was the recency of use. If participants chose the ‘never’ option, they skipped the remaining questions about
their usage of that substance and went to the questions about their usage of the next substance. Besides these relevant questions for the current study, some questions were also asked regarding eating habits, sporting behavior, music preference and emotional responses to situations, and masculinity. These questions were to be used to generate data for related studies by other researchers of the team. All questions were in English, since it was assumed that not all participants would be able to read Dutch at a high enough level to participate. However, as participants were expected to be students, English was expected to be at a high enough level for all participants to complete the questionnaire.

Some important disadvantages of using a questionnaire and thus self-report are that there is no way to tell if participants were being truthful, there is no way to tell how much thought participants put in and participants might have been forgetful of the details they were asked about. With regards to the truthfulness of answers of participants, there might for example be gender differences in how socially desirable it is to say that one did not use substances. The anonymity in this study should help eliminate most of the influence of social desirability, but it is possible it still had an effect. Furthermore, the questions were based on things that this author and their fellow researchers thought were important. Therefore, they might have missed something due to their bias.

Based on the research done earlier in the Netherlands (“Attitudes of Europeans towards tobacco and electronic cigarettes”, 2015; Van Laar et al., 2016; Van der Pol & Van Laar, 2015), the expectation was to find that approximately 89% of participants had used alcohol before, 54% of participants had used cigarettes before, 24% of participants had used cannabis before, 7.5% had used ecstasy before, 5% had used cocaine before and 4.5% had used amphetamine before. Some general trends that were expected based on this earlier research was to find that more men, more people with a higher level of education and more people living in more urban areas would report using substances before and also recent substance use, as compared to women, people with a lower level of education and people living in less urban areas (“Attitudes of Europeans towards tobacco and electronic cigarettes”, 2015; Van Laar et al., 2016; Van der Pol & Van Laar, 2015). These differences might be partially or entirely explained by the aforementioned possible differences in truthfulness between participants, since these studies also used questionnaires to gather data.

2.2.2 The Spaceship game
The Spaceship game was a video game used to measure the risk-taking behavior of the participants. For a visual representation of what the gameplay looked like, see Figure 5. The
participants were required to fly their spaceship through the galaxy while trying to avoid meteors. They used the arrow keys to control their ship. They could use the up and down keys to control the vertical movement of the spaceship. Using the left and right arrow keys, participants controlled the speed of the spaceship. By giving complete control of the movement of the spaceship over to participants, they were in control of errors and therefore the second requirement of Glendon et al. (1996) was met.

![Spaceship game screenshot](image)

*Figure 5. Screenshot of gameplay of the Spaceship game.*

The game had 13 different levels of difficulty. These differences in difficulty were based solely on the differences between the speeds the spaceship flew at. However, these differences in speed possibly also influenced the distance participants could keep to meteorites, since at higher speeds it would be more difficult to react quick enough to keep as large of a distance to them. The spaceship started at the lowest speed possible (difficulty level 1), which was 320 pixels per second. The speed could be increased or decreased at intervals of 50 pixels per second. The maximum speed was thus 920 pixels per second at difficulty level 13.

In the top-left corner of the screen the game displayed icons of the amount of shields the participant had left. This was done to clearly show the amount of protective measures there were. When the spaceship hit a meteor, one of the shields would be depleted and the display would also show one less shield. If a participant had no shields and the spaceship hit a meteor, the round was over. This was shown to the participants using an animation of the
spaceship exploding. This was supposed to indicate the destruction of their spaceship. The combination of the clear visual representation of the varying protective measures, and the consequence of hitting meteors of the spaceship eventually blowing up, the round being over and the loss of opportunity to gain more points should lead to a target level of risk for participants. This gives a good reason to suppose the participants are characterized by a target level of risk, and thus satisfies the first requirement of Glendon et al. (1996). Showing the varying amount of protective measures through a different amount of shields also helps test the first hypothesis as it makes participants aware of the protective measures in place. If their risk-taking behavior significantly differs between different amounts of shields they have, it will support that there is an effect of awareness of protective measures on risk-taking behavior.

The maximum duration of a session was four minutes. Thus, each session had two possible ways to end; a participant flew their spaceship into a meteor when they had no more shields and had their spaceship destroyed, or a participant was able to fly through the galaxy for four minutes without this happening. If the latter happened, participants were shown that their spaceship flew out of the far-right edge of the screen.

The game started with a viewing of a short example of gameplay. This was supposed to show an example of what the gameplay was like to participants before they started playing. After watching this, participants played a test round, which randomly assigned them either 0 shields, or 3 shields. This test round was supposed to let participants get a feel for the controls of the game, the visuals of the game, and the difficulty levels that were available to them. Once these warm-ups were done, participants played five rounds. In these rounds they were assigned 0, 1, 3, 4 and 5 shields. The order in which these shields were assigned was random. This was, among other reasons, done to help combat the effect on the data of a potential reduced attention level, since it could disturb the target level of risk of participants as mentioned by Glendon et al. (1996).

All data of the game was recorded with a sampling frequency of ten times per second and was saved in the ‘steplog’ files. These files saved all the data in a .csv format. This made the data usable with Microsoft Excel and the variables easy to transform into the needed variables for usage in SPSS. The game recorded all variables ten times each second and at the end of the sessions saved the data in files called ‘steplog.csv’. For each participant the ‘steplog.csv’ file containing their data ended up in a folder with the participant number they filled in as a name. This made sorting through the data more convenient and made it easier to
check whether any mistakes were made by participants when filling in their participant numbers.

2.3 Design

The study consisted of five within-subject conditions, which were the five separate rounds within the Spaceship game. In each condition, participants were given a different amount of shields (0, 1, 3, 4 or 5). Each participant went through each condition (0, 1, 3, 4 and 5 shields to start with) once. The assigning of the shield conditions was done in a random order by the Spaceship game itself. Neither the participants nor the researchers were aware of the order of the shield conditions. The study can thus be described as using a randomized design with five within-subject conditions.

The data that was gathered by the Spaceship game was used to calculate three variables that served as indicators of risk-taking behavior. The variables were speed, time to collision (TTC) and distance to the closest meteor (DCM). A measurement of distance to danger in both physical distance and time was used in this study with the aim to look at two often used and useful ways of measuring riskiness of behavior. In traffic people are often advised to keep a certain distance to, for example, other cars, traffic lights, and the sidewalk (Vogel, 2003). This way of measuring whether behavior is safe enough through looking at the amount of distance kept to danger, such as obstacles, is used here in the form of looking at physical distance to meteors (DCM). On the other hand a lot of research has looked at reaction times of human beings in risky situations, and riskiness of behavior is often judged by looking at how much time people leave for themselves to properly respond to danger. This way of measuring riskiness of behavior is represented here by the time to collision (TTC). The time to collision has also been used in other experiments. Especially tests regarding traffic safety often include the time to collision (TTC) as a measurement, and it has so far been proven to be a useful measurement in these settings (Vogel, 2003). Thus, it seems to be a tried and tested measurement to measure risk-taking behavior. Furthermore, it helps relate the behavior in the video game to that in real traffic settings.

DCM was defined as the distance to the closest meteor to the ship, regardless of which angle from the ship it was at. It was calculated using the x-coordinates of the closest meteorites on the x-axis, the y-coordinates of the closest meteorites on the y-axis and the y-coordinates of the ship on the y-axis. Speed was defined as the pixels per second the spaceship flew at. It was calculated using the difficulty level participants flew at. TTC was defined as the time until the spaceship would have collided with a meteor if it had not
changed its vertical position. It was calculated using the distance from the closest meteorites on the x-axis to the spaceship and the speed in pixels per second the spaceship flew at. Since this variable is somewhat more complicated, an example was included. Imagine if the ship was flying at the lowest difficulty level, and thus at 320 pixels per second, and the vertical position of the closest meteor on the screen was 429 pixels to the right of the left edge of the screen. First, you would have to take the 429 and detract the 109 pixels, leaving you with 320 pixels. Divided by the speed of 320 pixels per second, the time to collision (TTC) would be exactly 1 second. The three aforementioned variables were the dependent variables. The average of the value for each of the variables was calculated for each individual shield and each individual round for each participant. The formulas used to calculate the values for these variables can be found in Appendix B.

The number of shields a participant had was supposed to represent the perceived level of risk. The lower the amount of shields a participant had, the higher the perceived level of risk was. This was the independent variable of protective measures. The other independent variables were the answers on the questionnaire regarding participants’ use of certain substances; whether they used the substances and the recency-, frequency- and quantity of use of said substances. The risk-taking behavior of participants was considered higher when the value for the speed variable was higher, the value for the TTC variable was lower and the value for the DCM variable was lower.

2.4 Procedure

The experiment was done in the computer rooms of the faculty of social sciences of Leiden University, and was spread over four days of time for testing. The computers in the computer rooms were all very similar, and all used the same 21 inch displays. Furthermore, similar computer mice and keyboards were used. Participants were seated with at least one seat and computer of distance between them, so they would not distract each other during their participation. The experiment averagely took around 45 minutes for each participant. The time it took varied between participants due to a difference in their working speeds on the questionnaire and a difference in their time of survival in the Spaceship game.

Participants were first given the information letter and the informed consent form (Appendices C and D). The information letter was used to inform the participants about what they were going to do and inform them that their data would not be associated with their name. This guaranteed their anonymity. It also informed them that the post-it note they had received had their participant number on it, and to fill in this number when asked to fill in
their participant number by the game and questionnaire. The information letter also informed
the participants that they could stop participating at any time without having to give a reason,
as their participation was entirely voluntary. Once the information letter was read, the
participants were required to sign the informed consent form as proof of them consenting to
their participation under the aforementioned agreements.

After the informed consent was signed one of the researchers turned on the Spaceship
game. The game contained instructions on how to fly the spaceship and how to gain points
(Appendix E). The gaining of points each round was based on the speed (difficulty level)
participants were flying at, and their total time flying. Participants were instructed verbally
that the three participants with the highest total scores over all rounds combined would receive a prize; 50 euro for first place, 30 euro for second place and 10 euro for third place.
They were told to remember their participant number, as the winners would be called out based on their participant numbers. These monetary rewards for scoring the most points were chosen to give participants an extrinsic reason to want to take the risk of flying faster. The decision to make the rewards money was made since participants were mostly students and young adults. The assumption was that to the average student or young adult a prize like 50 euro, 30 euro, or 10 euro was considered to be a sizeable amount of money, since they would generally not have as much income as the average adult individual with a fulltime job. Therefore, the expectation was that participants would be motivated to take risks to gain these rewards.

Once the game was over, participants were instructed by the game to raise their hand. When they did this, the present researchers would put the questionnaire on for them. At the end of this questionnaire participants were reminded to remember their participant number, since these would be called out to collect their prize if they ended up in the top three of highest total scores.

When participants were done with the questionnaire, they could collect their money or credits (6.50 euro or 2 credits). They were given a debriefing letter (Appendix F) with a more detailed explanation of what the study was about and what we were trying to find. After receiving their credits and reading the debriefing letter, they were done and left. Once all the days of the experiments were done the winning participant numbers were determined. Then the participants were contacted by e-mail and awarded their cash prize.

2.5 Data analysis
The analyses in the current study were done using IBM SPSS Statistics 21. Checks were done to make sure no participants filled in the wrong participant number in the game or in the questionnaire, and it turned out that such a mistake had not occurred. No missing values were reported, and all data was included in the analyses.

The data from the questionnaire was re-coded into four variables per substance (alcohol, cigarettes, marijuana, cocaine, ecstasy and amphetamine): (1) Usage of the substance, (2) recency of use of the substance, (3) frequency of use of the substance and (4) quantity of use of the substance. Variable 1 for each substance was coded as a categorical variable with two categories (dichotomous variable): Never used a substance and used a substance. If participants never used a substance before, they were not included in the analyses of the hypotheses regarding the recency-, frequency-, and quantity of use of that substance, as their data would be irrelevant for these hypotheses. Variable 2 was coded for each substance as a categorical variable with three categories: low recency users, medium recency users, and high recency users. Variable 3 was coded for each substance as a categorical variable with three categories: low frequency users, medium frequency users, and high frequency users. Variable 4 was coded for each substance as a categorical variable with three categories: low quantity users, medium quantity users, and high quantity users. The divisions over the groups for variable 2, variable 3, and variable 4 differed between the substances, as some substances were assumed to be used more than others and thus also more recently. The divisions were based on observations made on websites of online substance user communities and the study done by Van Der Pol and Van Laar (2015) regarding the amount of drugs used in the Netherlands.

The Spaceship game saved all the data in the ‘steplog’ files. The game recorded several variables. These variables were participant number, session number, number of shields left, the position of the spaceship on the y-axis, the closest meteor on the y-axis, the closest meteor on the x-axis, time, the difficulty level, and the score in points. This data from the steplog was used to calculate the three variables used in this study to assess risk-taking behavior: speed, distance to the closest meteor (DCM) and the time to collision (TTC) (Appendix B).

The first hypothesis (1) was tested using several repeated measures ANOVA’s. This format was chosen since these tests correct for cumulative type-1 errors. A type-1 error is rejecting the null hypothesis, when it should not be rejected. When several tests are done, the chance of one or more of these tests finding a significant result by chance, and falsely rejecting the null hypothesis becomes larger. Such errors are known as cumulative type-1
errors. These errors can lead to a study finding significant effects that are, in fact, there by chance. It is therefore important to correct for cumulative type-1 errors, since it makes the results more reliable. Therefore, the correction for cumulative type-1 errors makes using repeated measures ANOVA’s more reliable than using paired sampled t-tests. The repeated measures ANOVA’s helped look for significant differences in the means of speed, DCM and TTC both between-conditions (comparing sessions with different amounts of starting shields) and within-conditions (comparing the amount of shields currently left within each session). The assumptions for using the repeated measures ANOVA were checked and the results of these checks will be reported in the results section.

Several other hypotheses (hypotheses 2A, 2C, 2D, 2E, 3A, 3c, 3D, 3E, 4A, 4C, 4D, 4E, 5A, 6A, and 7A) were tested using separate one-way ANOVA’s for all three risk-taking variables (speed, DCM, and TTC). The assumptions for using the one-way ANOVA were checked and the results of these checks will be reported in the results section.

For the remaining last hypotheses (hypotheses 2B, 3B, 4B, 5B, 6B, and 7B) the file was split into users and non-users of the substance relevant for the hypothesis that was being tested using SPSS. Once this was done, several repeated measures ANOVA’s were used for these different groups. For hypothesis 7B it turned out that there were too few participants in the amphetamine users group to do a repeated measures ANOVA, and thus a Friedman test was used instead.

Finally, for each and every test that was used a post hoc power analysis was done using Gpower (Faul & Erdfelder, 1992). This was done to check whether the tests would be able to detect a small effect (f = .10), medium effect (f = .25) and large effect (f = .40) as according to Cohen (1977, 1988). The Gpower manual (G*POWER 3.1 manual, 2014) indicated using the same effect sizes in the program as Cohen (1977), and thus the program was used for these tests. If no significant effect was found and the power of the tests was found to be lacking, this will be discussed in the discussion.

3. Results

3.1 Assumptions of used statistical analyses

3.1.1 Assumptions of the repeated measures ANOVA
(1) The assumption of having the dependent variables be measured on a continuous scale is met, since the variables speed, DCM and TTC are measured on a continuous scale. (2) The
The assumption of having the within-subject factor being categorical with at least two levels is also met. (3) The assumption of having no significant outliers in any level of the within-subjects factor was not tested, as outliers would be related to the phenomenon that is being researched. (4) The assumption of normal distribution of the dependent variables (speed, DCM and TTC) was measured through the use of normal Q-Q plots. The dependent variables have been shown to be normally distributed. (5) The final assumption of sphericity has been checked for each analysis using Mauchly’s test. In the cases where Mauchly’s test showed that sphericity was not met for that analysis, it will be reported and it will be mentioned what correction was used.

3.1.2 Assumptions of the Friedman test

For amphetamine the users group was too small to test for sphericity with Mauchly’s sphericity test. Multivariate tests also did not yield any results, due to a lack of degrees of freedom. Thus, the choice was made to use the Friedman test, since the assumptions of normal repeated measures ANOVA were violated and the Friedman test is known to be more robust to such issues. However, the Friedman test does have some assumptions. These will be checked here.

(1) The assumption of having one group that is measured on three or more different occasions is met, since it is done for the group of amphetamine users and for DCM, speed and TTC the outcomes were measured on five occasions (5 shields condition, 4 shields condition, 3 shields condition, 1 shield condition, and 0 shields condition). (2) Since only a few criteria (no neurological issues and no previous experience with the game) were used for sampling, the assumption of the group being a random sample from the population of amphetamine users is met. (3) The dependent variables are on a continuous level (DCM, speed and TTC), and thus meet the assumption of needing to be on a ordinal or continuous level. (4) It is unsure whether the sample is normally distributed, and this meets the assumption that it is not necessary to be normally distributed.

3.1.3 Assumptions of the one-way ANOVA

(1) The assumption of having the dependent variables be on an interval or ratio level is met, since the variables speed, DCM and TTC are all on interval or ratio level. (2) The assumption of the independent variables (usage of the substance, recency of use of the substance, frequency of use of the substance and quantity of use of the substance) being categorical and having at least two or more independent groups is also met. (3) The
The assumption of independence of observations is met. (4) The assumption of having no significant univariate- or multivariate outliers was not tested, as outliers would be related to the phenomenon that is being researched. (5) The assumption of approximately normal distribution for each category of the independent variables was tested using Shapiro-Wilks tests. In several cases the dependent variables were not normally distributed for the categories of the independent variables. It happened mostly for larger groups and the DCM variable. Since the one-way ANOVA is robust to deviations of normality, the analyses were done regardless of some cases of non-normality. The results will be reported with the non-normality for larger groups and the DCM variable in mind. (6) The assumption of homogeneity of variances was tested for each analysis using Levene’s test for homogeneity of variances, and the results and subsequent decisions that were made will be reported for each analysis.

3.2 Hypothesis 1: Being aware of higher levels of protection is related to more risk-taking behavior

3.2.1 Comparison between shield conditions

The presence of a risk homeostasis effect was measured for both the long term as well as the short term. A long-term effect was defined as an effect of being in the different sessions starting out with more or less shields, or protective measures, on risk-taking behavior. The presence of risk compensation in this case would indicate that there would be an effect of being aware of the amount protective measures someone gets on their risk-taking in this setting. A short-term effect would be an effect of having different amounts of shields, or protective measures, left within sessions on risk-taking behavior. This was done to see if the lagged feedback Wilde (1982) spoke about would still be observed in this setting. If risk compensation would be observed in the short term, it would indicate that people more frequently update their risk-taking behavior in this setting than the model of Wilde (1982) would lead us to expect.

First, a look was taken at the relatively more long-term risk homeostasis effect. To find out if this long-term risk homeostasis effect was present a comparison was made between the conditions with different amounts of starting shields using repeated measures ANOVA’s. The dependent variables for these three tests were the DCM, speed and TTC variables.
Distance to the closest meteor (DCM)

An one-way repeated measures ANOVA was used (N = 69) to compare mean DCM between shield condition 5 (5 shields at start, $M = 218.80, SD = 11.48$), shield condition 4 (4 shields at start, $M = 221.08, SD = 12.56$), shield condition 3 (3 shields at start, $M = 223.97, SD = 15.95$), shield condition 1 (1 shield at start, $M = 231.33, SD = 27.65$), and shield condition 0 (0 shields at start, $M = 261.89, SD = 71.55$). Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 321.12, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .34$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.35, 91.46) = 21.66, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .62, $F (4, 65) = 10.00, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 3 shields condition ($p = .023$), the 1 shield condition ($p = .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shield condition and the 1 shield condition ($p = .011$) and the 0 shields condition ($p < .001$). The next significant result was found between the 3 shields condition and the 0 shields condition ($p < .001$). The final significant result was found between the 1 shield condition and the 0 shields condition ($p = .002$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .14 for a small effect ($f = .10$), .62 for a medium effect ($f = .25$), and .96 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium and small effect as according to Cohen (1977). As can be seen in the graph (Figure 6), the significant effects indicate an increase in mean DCM when starting with fewer shields.
Figure 6. Graph of comparison between shield conditions - DCM

Speed
An one-way repeated measures ANOVA was used (N = 69) to compare mean speeds between shield condition 5 (5 shields at start, $M = 528.61$, $SD = 112.42$), shield condition 4 (4 shields at start, $M = 521.22$, $SD = 160.73$), shield condition 3 (3 shields at start, $M = 503.39$, $SD = 139.59$), shield condition 1 (1 shield at start, $M = 467.36$, $SD = 121.77$), and shield condition 0 (0 shields at start, $M = 432.49$, $SD = 112.42$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed ($F(4, 272) = 17.44$, $p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .56, $F(4, 65) = 13.05$, $p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < 0.001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .005$) and the 0 shields condition ($p < .001$). The final significant result was found between the 3 shields condition and the 0 shields condition ($p < .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .22 for a small effect ($f = .10$), .92 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small
As can be seen in the graph (Figure 7), the significant effects indicate a decrease in mean speed when starting with fewer shields.

### Time to collision (TTC)

An one-way repeated measures ANOVA was used (N = 68) to compare mean TTC between shield condition 5 (5 shields at start, $M = .85, SD = .23$), shield condition 4 (4 shields at start, $M = .88, SD = .27$), shield condition 3 (3 shields at start, $M = .91, SD = .25$), shield condition 1 (1 shield at start, $M = .98, SD = .23$), and shield condition 0 (0 shields at start, $M = 1.06, SD = .27$). Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 18.86, p = .026$), therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon = .89$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F (3.77, 252.35) = 17.42, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .56, $F (4, 64) = 12.47, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < .001$) and the 0 shield condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .012$) and the 0 shields condition ($p < 0.001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). The final significant result was found between the 1 shield condition and the 0 shields condition ($p = .026$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level
used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .21 for a small effect ($f = .10$), .89 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977). As can be seen in the graph (Figure 8), the significant effects indicate an increase in mean TTC when starting with fewer shields.

![Figure 8. Graph of comparison between shield conditions - TTC](image)

### 3.2.2 Comparison between shields left within shield conditions

Secondly a look was taken at the relatively more short-term risk homeostasis effect. To find out if this was present a comparison was made within each condition between the amounts of shields left using repeated measures ANOVA’s. The dependent variables for these tests were the DCM, speed and TTC variables. The decision was made to omit the first shield in every condition for the comparisons of DCM and TTC, since the data for these conditions was distorted. The likely cause was the fact that the formulas for these variables used the distance from the spaceship to meteorites. These formulas did not correct for the fact that at the start of each session no meteorites would be on the screen yet. Therefore, the DCM and TTC for the first shield of each condition were deemed unreliable and were not used in the comparisons. This unfortunately led to data for the one shield condition only being usable for the speed variable. Furthermore, the condition with no shields was not included in the analyses, since it only had one option for the amount of shields left and thus could not be compared to any other amount of shields left within the condition.
Distance to the closest meteor (DCM)

5 shields condition
An one-way repeated measures ANOVA was used (N = 63) to compare mean DCM at shield 4 (M = 207.89, SD = 13.90), shield 3 (M = 205.25, SD = 18.84), shield 2 (M = 207.48, SD = 12.93), shield 1 (M = 205.43, SD = 14.42), and no shields (M = 205.65, SD = 17.47). The univariate results showed that there was no significant effect of the amount of shields people had left in the 5 shield condition on the mean DCM (F (4, 248) = .46, p = .768). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .97, F (4, 59) = .39, p = .812). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .23 for a small effect (f =.10), .90 for a medium effect (f = .25), and 1 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977).

4 shields condition
An one-way repeated measures ANOVA was used (N = 58) to compare mean DCM at shield 3 (M = 207.95, SD = 17.37), shield 2 (M = 206.97, SD = 14.50), shield 1 (M = 207.33, SD = 17.08), and no shields (M = 209.24, SD = 14.52). The univariate results showed that there was no significant effect of the amount of shields people had left in the 4 shield condition on the mean DCM (F (3, 171) = .26, p = .852). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .98, F (3, 55) = .30, p = .825). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .19 for a small effect (f =.10), .87 for a medium effect (f = .25), and 1 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977).

3 shields condition
An one-way repeated measures ANOVA was used (N = 58) to compare mean DCM at shield 2 (M = 203.31, SD = 16.43), shield 1 (M = 202.83, SD = 16.21), and no shields (M = 205.08, SD = 12.37). The univariate results showed that there was no significant effect of the amount
of shields people had left in the 3 shield condition on the mean DCM ($F (2, 114) = .36, p = .697$). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .98, $F (2, 56) = .45, p = .640$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .17 for a small effect ($f = .10$), .78 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

**Speed**

5 shields condition

An one-way repeated measures ANOVA was used ($N = 63$) to compare mean speeds at shield 5 ($M = 456.74, SD = 119.29$), shield 4 ($M = 555.47, SD = 172.89$), shield 3 ($M = 576.11, SD = 183.92$), shield 2 ($M = 585.34, SD = 181.86$), shield 1 ($M = 590.94, SD = 172.35$), and no shields ($M = 592.98, SD = 184.65$). Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (14) = 214.66, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .50$). The univariate results showed that there was a significant effect of the amount of shields people had left in the 5 shield condition on the mean speed ($F (2.50, 155.29) = 36.09, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .44, $F (5, 58) = 14.50, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between 5 shields left and all the other amounts of shields left (all $p < .001$). Another significant effect was found between 4 shields left and 2 shields left ($p = .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .16 for a small effect ($f = .10$), .76 for a medium effect ($f = .25$), and .99 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977). However, as can be seen in the graph (Figure 9), the significant effects indicate an increase in mean speed when losing shields.
4 shields condition

An one-way repeated measures ANOVA was used (N = 57) to compare mean speeds at shield 4 ($M = 473.80$, $SD = 142.83$), shield 3 ($M = 578.08$, $SD = 195.87$), shield 2 ($M = 586.18$, $SD = 178.60$), shield 1 ($M = 594.91$, $SD = 184.60$), and no shields ($M = 595.49$, $SD = 183.13$). Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 113.00, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .52$). The univariate results showed that there was a significant effect of the amount of shields people had left in the 4 shield condition on the mean speed ($F (2.06, 115.31) = 36.82, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .43, $F (4, 53) = 17.28, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between 4 shields left and all the other amounts of shields left (all $p < .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .14 for a small effect ($f = .10$), .66 for a medium effect ($f = .25$), and .97 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977). However, as can be seen in the graph (Figure 10), the significant effects indicate an increase in mean speed when losing shields.

Figure 9. Graph of comparison of amount of shields left within 5 shields condition - speed
Figure 10. Graph of comparison of amount of shields left within 4 shields condition - speed

3 shields condition

An one-way repeated measures ANOVA was used (N = 58) to compare mean speeds at shield 3 (\(M = 458.06, SD = 113.27\)), shield 2 (\(M = 556.83, SD = 171.12\)), shield 1 (\(M = 596.79, SD = 185.98\)), and no shields (\(M = 608.20, SD = 179.44\)). Mauchly's test indicated that the assumption of sphericity had been violated (\(\chi^2(5) = 62.85, p < .001\)), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (\(\epsilon = .61\)). The univariate results showed that there was a significant effect of the amount of shields people had left in the 3 shield condition on the mean speed (\(F(1.83, 104.46) = 49.58, p < .001\)). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .41, \(F(3, 55) = 26.45, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between 3 shields left and all the other amount of shields left (all \(p < .001\)). Two other significant effects were found between 2 shields left and both 1 shield left and no shields left (both \(p = .001\)). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .14 for a small effect (\(f = .10\)), .62 for a medium effect (\(f = .25\)), and .96 for a large effect (\(f = .40\)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977). However, as can be seen in the graph (Figure 11), the significant effects indicate an increase in mean speed when losing shields.
An one-way repeated measures ANOVA was used (N = 69) to compare mean speeds at shield 1 ($M = 440.20, SD = 110.43$), and no shields ($M = 524.69, SD = 164.87$). The univariate results showed that there was a significant effect of the amount of shields people had left in the 1 shield condition on the mean speed ($F (1, 68) = 51.99, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks’ Lambda = .57, $F (1, 68) = 51.99, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between 1 shield left and no shields left ($p < .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .90 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977). However, as can be seen in the graph (Figure 12), the significant effects indicate an increase in mean speed when losing shields.
Figure 12. Graph of comparison of amount of shields left within 1 shield condition - speed

Time to collision (TTC)

5 shields condition

An one-way repeated measures ANOVA was used (N = 63) to compare mean TTC at shield 4 (M = .80, SD = .28), shield 3 (M = .74, SD = .28), shield 2 (M = .73, SD = .27), shield 1 (M = .71, SD = .24), and no shields (M = .71, SD = .28). Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 33.66, p < .001$), therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon = .78$). The univariate results showed that there was a significant effect of the amount of shields people had left in the 5 shield condition on the mean TTC ($F (3.32, 205.67) = 4.23, p = .005$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .79, $F (4, 59) = 4.03, p = .006$). The post-hoc Bonferroni pairwise comparisons showed significant differences between 4 shields left and 2 shields left ($p = .011$), 1 shield left ($p = .038$) and no shields left ($p = .020$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .20 for a small effect ($f = .10$), .89 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977). However, as can be seen in the graph (Figure 13), the significant effects indicate a decrease in mean TTC when losing shields.
An one-way repeated measures ANOVA was used (N = 57) to compare mean TTC at shield 3 (M = .74, SD = .28), shield 2 (M = .73, SD = .29), shield 1 (M = .72, SD = .27), and no shields (M = .73, SD = .27). Mauchly's test indicated that the assumption of sphericity had been violated (\(\chi^2(5) = 16.53, p = .005\)), therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity (\(\varepsilon = .84\)). The univariate results showed that there was no significant effect of the amount of shields people had left in the 4 shield condition on the mean TTC (\(F(2.64, 147.97) = .23, p = .852\)). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .98, \(F(3, 54) = .31, p = .816\)). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .17 for a small effect (\(f = .10\)), .81 for a medium effect (\(f = .25\)), and 1 for a large effect (\(f = .40\)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977).

3 shields condition
An one-way repeated measures ANOVA was used (N = 58) to compare mean TTC at shield 2 (M = .75, SD = .34), shield 1 (M = .69, SD = .31), and no shields (M = .70, SD = .29). The univariate results showed that there was no significant effect of the amount of shields people had left in the 4 shield condition on the mean TTC (\(F(2, 114) = 2.24, p = .111\)).
of the multivariate approach also showed no significant effect (Wilks' Lambda = .93, $F (2, 56) = 2.15, p = .126$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .17 for a small effect ($f = .10$), .78 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

### 3.3 Hypothesis 2: Risk-taking and alcohol use

#### 3.3.1 Hypothesis 2A: Users of alcohol show more risk-taking behavior than non-users.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of alcohol; users (N = 64) versus non-users (N = 5).

**Distance to the closest meteor (DCM)**

An one-way ANOVA was conducted to compare mean DCM between users ($M = 221.20$, $SD = 13.14$) and non-users ($M = 224.24$, $SD = 9.90$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .682$). The univariate results showed that there was no significant effect of whether people use alcohol or not on the mean DCM ($F (1, 67) = .25, p = .616$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was conducted to compare mean speed between users ($M = 485.31$, $SD = 109.93$) and non-users ($M = 489.08$, $SD = 167.61$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .088$). The univariate results showed that there was no significant effect of whether people use alcohol or not on the mean speed.
(F(1, 67) = .01, p = .943). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**
An one-way ANOVA was conducted to compare mean TTC between users (M = .94, SD = .20) and non-users (M = 1.01, SD = .25). Levene’s test showed that the assumption of homogeneity of variances was met (p = .755). The univariate results showed that there was no significant effect of whether people use alcohol or not on the mean TTC (F(1, 67) = .51, p = .479). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

3.3.2 **Hypothesis 2B: Usage of alcohol influences the risk-compensation strategy.**
Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of alcohol; users (N = 64) versus non-users (N = 5) and three separate analyses were done for each group.

**Distance to the closest meteor (DCM)**
An one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both alcohol non-users and users. The means and standard deviations can be found in the table (Table 1). For non-users Mauchly's test indicated that the assumption of sphericity had been violated (χ²(9) = 19.91, p = .044), therefore degrees of freedom were
corrected using Greenhouse-Geisser estimates of sphericity (ε = .41). The univariate results showed that there was no significant effect of the amount of shields people started with on the mean DCM \((F (1.63, 6.51) = 3.59, p = .094)\). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .01, \(F (4, 1) = 37.26, p = .122\)). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .05 for a small effect (\(f = .10\)), .07 for a medium effect (\(f = .25\)), and .11 for a large effect (\(f = .40\)) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

For users Mauchly’s test indicated that the assumption of sphericity had been violated \((\chi^2 (9) = 306.90, p < .001)\), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity (\(ε = .33\)). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM \((F (1.33, 83.93) = 19.63, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .62, \(F (4, 60) = 9.05, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 3 shields condition \((p = .033)\) and the 1 shield condition \((p = .002)\) and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 1 shield condition \((p = .018)\) and the 0 shields condition \((p < .001)\). The next significant effect was found between the 3 shields condition and the 0 shields condition \((p < .001)\). The final significant effect was found between the 1 shield condition and the 0 shields condition \((p = .004)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect (\(f = .10\)), .57 for a medium effect (\(f = .25\)), and .93 for a large effect (\(f = .40\)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 14), there is an increase in mean DCM when starting with less shields for users and non-users. However, it was only found to be significant for users and not for non-users. On top of that, the differences appear to be very minimal.
**Figure 14.1.** Graph of comparison of shield conditions between alcohol users and non-users – DCM

**Table 1.** Table of means and standard deviations: overall, alcohol users and non-users - DCM

<table>
<thead>
<tr>
<th>Shield Condition</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Alcohol M</th>
<th>Alcohol SD</th>
<th>No alcohol M</th>
<th>No alcohol SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>218.62</td>
<td>11.82</td>
<td>221.03</td>
<td>5.69</td>
</tr>
<tr>
<td>4 shields</td>
<td>221.08</td>
<td>12.56</td>
<td>220.71</td>
<td>12.13</td>
<td>225.83</td>
<td>18.27</td>
</tr>
<tr>
<td>3 shields</td>
<td>223.97</td>
<td>15.95</td>
<td>223.92</td>
<td>16.42</td>
<td>224.59</td>
<td>8.77</td>
</tr>
<tr>
<td>1 shield</td>
<td>231.33</td>
<td>27.65</td>
<td>231.18</td>
<td>27.83</td>
<td>233.28</td>
<td>28.30</td>
</tr>
<tr>
<td>0 shields</td>
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<td>71.55</td>
<td>262.42</td>
<td>74.05</td>
<td>255.09</td>
<td>24.42</td>
</tr>
</tbody>
</table>

**Speed**

An one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both alcohol non-users and users. The means and standard deviations can be found in the table (Table 2). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed ($F(4, 16) = 4.95, p = .009$). The results of the multivariate approach showed no significant effect (Wilks' Lambda = .07, $F(4, 1) = 3.37, p = .385$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was $.06$ for a small effect ($f = .10$), $.09$ for a medium effect ($f = .25$), and $.17$ for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of $.80$) for a large...
effect, medium effect and small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \((F(4, 252) = 14.84, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .57, \(F(4, 60) = 11.31, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition \((p = .004)\) and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 1 shield condition \((p = .016)\) and the 0 shields condition \((p < .001)\). The final significant effect was found between the 3 shields condition and the 0 shields condition \((p < .001)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .21 for a small effect \((f = .10)\), .90 for a medium effect \((f = .25)\), and 1 for a large effect \((f = .40)\) as according to Cohen (1988).

Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977). As can be seen in the graph (Figure 15), there is a decrease in mean speed when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.

![Graph of comparison of shield conditions between alcohol users and non-users – speed](image)

*Figure 15.2. Graph of comparison of shield conditions between alcohol users and non-users – speed*

<p>| Table 2. Table of means and standard deviations: overall, alcohol users and non-users – speed |
|-----------------------------------------------|---------|---------|---------|</p>
<table>
<thead>
<tr>
<th>Overall</th>
<th>Alcohol</th>
<th>No alcohol</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>---------</td>
<td>---------</td>
<td>------------</td>
</tr>
</tbody>
</table>
52
### Time to collision (TTC)

An one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both alcohol non-users and users. The means and standard deviations can be found in the table (Table 3). For non-users the univariate results showed that there was no significant effect of the amount of shields people started with on the mean TTC ($F(4, 16) = 2.86, p = .058$). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .01, $F(4, 1) = 19.48, p = .168$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .06 for a small effect ($f = .10$), .09 for a medium effect ($f = .25$), and .17 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

For users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2(9) = 23.03, p = .006$), therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon = .86$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F(3.68, 228.28) = 14.99, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .58, $F(4, 59) = 10.61, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p = .003$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .042$) and the 0 shields condition ($p < .001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p = .001$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .025$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .19 for a small effect ($f = .10$), .86 for a medium effect ($f = .25$), and 1 for a large effect.
effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not for a small effect as according to Cohen (1977). As can be seen in the graph (Figure 16), there is an increase in mean TTC when starting with less shields for users and non-users. However, it was only found to be significant for users and not for non-users. There is a clear difference between the users and the non-users.

![Graph of comparison of shield conditions between alcohol users and non-users – TTC](image)

*Figure 16. Graph of comparison of shield conditions between alcohol users and non-users – TTC*

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Alcohol M</th>
<th>Alcohol SD</th>
<th>No alcohol M</th>
<th>No alcohol SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
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<td>.27</td>
<td>.85</td>
<td>.24</td>
<td>.83</td>
<td>.22</td>
</tr>
<tr>
<td>4 shields</td>
<td>.88</td>
<td>.23</td>
<td>.88</td>
<td>.26</td>
<td>.94</td>
<td>.45</td>
</tr>
<tr>
<td>3 shields</td>
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<td>.25</td>
<td>.91</td>
<td>.25</td>
<td>.91</td>
<td>.32</td>
</tr>
<tr>
<td>1 shield</td>
<td>.97</td>
<td>.27</td>
<td>.96</td>
<td>.22</td>
<td>1.14</td>
<td>.26</td>
</tr>
<tr>
<td>0 shields</td>
<td>1.06</td>
<td>.23</td>
<td>1.05</td>
<td>.27</td>
<td>1.16</td>
<td>.29</td>
</tr>
</tbody>
</table>

### 3.3.3 Hypothesis 2C: More recent use of alcohol is related to higher risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the recency of use of alcohol; low recency users (N = 13), medium recency users (N = 8), and high recency users (N = 43).

Distance to the closest meteor (DCM)
An one-way ANOVA was used to compare mean DCM between low recency users (1 month or more ago, \( M = 222.72, SD = 11.30 \)), medium recency users (8 days – 1 month ago, \( M = 225.12, SD = 21.64 \)) and high recency users (1 week or less ago, \( M = 220.01, SD = 11.81 \)). Levene’s test showed that the assumption of homogeneity of variances was met (\( p = .173 \)). The univariate results showed that there was no significant effect of the recency of use of alcohol on the mean DCM (\( F (2, 61) = .61, p = .546 \)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .10 for a small effect (\( f = .10 \)), .40 for a medium effect (\( f = .25 \)), and .80 for a large effect (\( f = .40 \)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between low recency users (1 month or more ago, \( M = 473.58, SD = 80.41 \)), medium recency users (8 days – 1 month ago, \( M = 516.26, SD = 156.61 \)) and high recency users (1 week or less ago, \( M = 483.09, SD = 109.37 \)). Levene’s test showed that the assumption of homogeneity of variances was met (\( p = .106 \)). The univariate results showed that there was no significant effect of the recency of use of alcohol on the mean speed (\( F (2, 61) = .39, p = .677 \)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .10 for a small effect (\( f = .10 \)), .40 for a medium effect (\( f = .25 \)), and .80 for a large effect (\( f = .40 \)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between low recency users (1 month or more ago, \( M = .96, SD = .17 \)), medium recency users (8 days – 1 month ago, \( M = .93, SD = .29 \)) and high recency users (1 week or less ago, \( M = .94, SD = .20 \)). Levene’s test showed that the assumption of homogeneity of variances was met (\( p = .183 \)). The univariate results
showed that there was no significant effect of the recency of use of alcohol on the mean TTC ($F(2, 61) = .07, p = .932$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .40 for a medium effect ($f = .25$), and .80 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

3.3.4 Hypothesis 2D: More frequent use of alcohol is related to higher risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the frequency of use of alcohol: low frequency users ($N = 12$), medium frequency users ($N = 21$), and high frequency users ($N = 31$).

Distance to the closest meteor (DCM)

An one-way ANOVA was used to compare mean DCM between low frequency users (once every 1 month or less, $M = 222.84, SD = 11.79$), medium frequency users (once every 1 week – 1 month, $M = 222.02, SD = 15.07$) and high frequency users (once every 6 days or more, $M = 220.01, SD = 12.54$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .578$). The univariate results showed that there was no significant effect of the frequency of use of alcohol on the mean DCM ($F(2, 61) = .25, p = .777$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .40 for a medium effect ($f = .25$), and .80 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

Speed

An one-way ANOVA was used to compare mean speed between low frequency users (once every 1 month or less, $M = 463.33, SD = 74.59$), medium frequency users (once every 1
week – 1 month, $M = 510.37$, $SD = 130.68$) and high frequency users (once every 6 days or more, $M = 476.84$, $SD = 106.05$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .128$). The univariate results showed that there was no significant effect of the frequency of use of alcohol on the mean speed ($F (2, 61) = .87, p = .422$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .40 for a medium effect ($f = .25$), and .80 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

Time to collision (TTC)

An one-way ANOVA was used to compare mean TTC between low frequency users (once every 1 month or less, $M = .98$, $SD = .17$), medium frequency users (once every 1 week – 1 month, $M = .91$, $SD = .23$) and high frequency users (once every 6 days or more, $M = .96$, $SD = .20$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .463$). The univariate results showed that there was no significant effect of the frequency of use of alcohol on the mean TTC ($F (2, 61) = .61, p = .545$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .40 for a medium effect ($f = .25$), and .80 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

3.3.5 Hypothesis 2E: Usage of higher quantities of alcohol per time is related to higher risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the quantity of use of alcohol per time; low quantity users ($N = 38$), medium quantity users ($N = 19$), and high quantity users ($N = 7$).
Distance to the closest meteor (DCM)
An one-way ANOVA was used to compare mean DCM between low quantity users (3 standard drinks or less, \( M = 219.17, SD = 8.73 \)), medium quantity users (3 standard drinks – 5 standard drinks, \( M = 225.56, SD = 20.06 \)) and high quantity users (5 standard drinks or more, \( M = 220.41, SD = 6.96 \)). Levene’s test showed that the assumption of homogeneity of variances was violated (\( p = .003 \)). Therefore the results of the Welch ANOVA were used. The univariate results showed that there was no significant effect of the quantity of use of alcohol per time on the mean DCM (\( F(2, 61) = 1.54, p = .434 \)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .10 for a small effect (\( f = .10 \)), .40 for a medium effect (\( f = .25 \)), and .80 for a large effect (\( f = .40 \)) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

Speed
An one-way ANOVA was used to compare mean speed between low quantity users (3 standard drinks or less, \( M = 470.88, SD = 96.18 \)), medium quantity users (3 standard drinks – 5 standard drinks, \( M = 530.59, SD = 134.03 \)) and high quantity users (5 standard drinks or more, \( M = 440.69, SD = 76.37 \)). Levene’s test showed that the assumption of homogeneity of variances was met (\( p = .053 \)). The univariate results showed that there was no significant effect of the quantity of use of alcohol per time on the mean speed (\( F(2, 61) = 2.65, p = .079 \)). Since there was a trend towards a difference between the different means, a look was taken at the post-hoc Bonferroni pairwise comparisons. This showed that the largest differences were to be found between the medium quantity users and the low quantity users (\( p = .156 \)), and the medium quantity users and the high quantity users (\( p = .188 \)). Since this interesting trend was found, a graph was made to visually showcase this trend (Figure 17). This graph shows the trend of fluctuation of mean speed between the groups. However, since the high quantity users group was quite small (\( N = 7 \)) and the other groups were not very large either, it is important to study this effect again with larger groups. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .10 for a small effect (\( f = .10 \)), .40 for a medium effect (\( f = .25 \)), and
.80 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

Figure 173. Graph of comparison between different quantity alcohol user groups – speed

A boxplot (Figure 18) was added to visually display the spread of the data, and it shows that the high quantity users are generally showing lower speeds and are close to being completely outside of the spread of the medium quantity users. However, they do have two outliers skewing the data. The larger outlier is making the trend less apparent by having a relatively high speed. Low quantity users are also clearly showing a lower speed, although they seem be a bit closer to the spread of medium quantity users. This might have to do with the low quantity users group being larger (N = 38) than the high quantity users group (N = 7).
Time to collision (TTC)

An one-way ANOVA was used to compare mean TTC between low quantity users (3 standard drinks or less, $M = .97, SD = .19$), medium quantity users (3 standard drinks – 5 standard drinks, $M = .87, SD = .23$) and high quantity users (5 standard drinks or more, $M = 1.02, SD = .18$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .366$). The univariate results showed that there was no significant effect of the quantity of use of alcohol per time on the mean TTC ($F (2, 61) = 2.14, p = .127$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .40 for a medium effect ($f = .25$), and .80 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

3.4 Hypothesis 3: Risk-taking and cigarettes use
3.4.1 Hypothesis 3A: Users of cigarettes show more risk-taking behavior than non-users.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of cigarettes; users (N = 31) versus non-users (N = 38).

Distance to the closest meteor (DCM)

An one-way ANOVA was used to compare mean DCM between users (M = 221.02, SD = 12.23) and non-users (M = 221.75, SD = 13.58). Levene’s test showed that the assumption of homogeneity of variances was met (p = .330). The univariate results showed that there was no significant effect of whether people use cigarettes or not on the mean DCM (F (1, 67) = .05, p = .819). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

Speed

An one-way ANOVA was used to compare mean speed between users (M = 503.42, SD = 117.02) and non-users (M = 471.03, SD = 109.68). Levene’s test showed that the assumption of homogeneity of variances was met (p = .466). The univariate results showed that there was no significant effect of whether people use cigarettes or not on the mean speed (F (1, 67) = 1.40, p = .241). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).
Time to collision (TTC)
An one-way ANOVA was used to compare mean TTC between users ($M = .92, SD = .22$) and non-users ($M = .97, SD = .19$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .330$). The univariate results showed that there was no significant effect of whether people use cigarettes or not on the mean TTC ($F(1, 67) = .95, p = .334$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not for a medium effect and small effect as according to Cohen (1977).

3.4.2 Hypothesis 3B: Usage of cigarettes influences the risk-compensation strategy.
Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of cigarettes; users ($N = 31$) versus non-users ($N = 38$) and three separate analyses were done for each group.

Distance to the closest meteor (DCM)
An one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cigarettes non-users and users. The means and standard deviations can be found in the table (Table 4). For non-users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 191.40, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .31$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F(1.22, 45.25) = 13.99, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .64, $F(4, 34) = 4.82, p = .003$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition ($p = .003$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .032$) and the 0 shields condition ($p = .002$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p = .007$). The final significant effect was found between the 1
shield condition and the 0 shields condition \( (p = .015) \). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .10 for a small effect \( (f = .10) \), .35 for a medium effect \( (f = .25) \), and .72 for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was inadequate power \( \text{i.e., power of .80} \) for a large effect, medium effect and small effect as according to Cohen (1977).

For users Mauchly's test indicated that the assumption of sphericity had been violated \( (\chi^2 (9) = 148.86, p < .001) \), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity \( (\epsilon = .36) \). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM \( (F (1.42, 42.56) = 8.30, p = .003) \). The results of the multivariate approach also showed a significant effect \( (\text{Wilks' Lambda} = .47, F (4, 27) = 7.63, p < .001) \). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition \( (p = .012) \). The other significant effect was found between the 3 shields condition and the 0 shields condition \( (p = .040) \). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .09 for a small effect \( (f = .10) \), .32 for a medium effect \( (f = .25) \), and .67 for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was inadequate power \( \text{i.e., power of .80} \) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 19), there is an increase in mean DCM when starting with less shields for users and non-users. However, the differences do appear to be very minimal.
Figure 195. Graph of comparison of shield conditions between cigarettes users and non-users – DCM

Table 4. Table of means and standard deviations: overall, cigarettes users and non-users - DCM

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Cigarettes</th>
<th>No cigarettes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>217.92</td>
</tr>
<tr>
<td>4 shields</td>
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<td>15.95</td>
<td>222.59</td>
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<td>27.65</td>
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</tr>
<tr>
<td>0 shields</td>
<td>261.89</td>
<td>71.55</td>
<td>262.29</td>
</tr>
</tbody>
</table>

Speed

An one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cigarettes non-users and users. The means and standard deviations can be found in the table (Table 5). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \((F(4, 148) = 11.10, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .51, \(F(4, 34) = 8.09, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition \((p = .006)\) and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 0 shields condition \((p = .002)\). The final
significant effect was found between the 3 shields condition and the 0 shields condition \( (p = .003) \). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .13 for a small effect \( (f = .10) \), .66 for a medium effect \( (f = .25) \), and .98 for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \( (F (4, 120) = 7.36, p < .001) \). The results of the multivariate approach also showed a significant effect \( (\text{Wilks' Lambda} = .52, F (4, 27) = 6.28, p = .001) \). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition \( (p = .007) \). The other significant effect was found between the 4 shields condition and the 0 shields condition \( (p < .001) \). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .12 for a small effect \( (f = .10) \), .55 for a medium effect \( (f = .25) \), and .95 for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 20), there is a decrease in mean speed when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.
Figure 206. Graph of comparison of shield conditions between cigarettes users and non-users – speed

Table 5. Table of means and standard deviations: overall, cigarettes users and non-users - speed

<table>
<thead>
<tr>
<th></th>
<th>5 shields</th>
<th>4 shields</th>
<th>3 shields</th>
<th>1 shield</th>
<th>0 shields</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>528.61</td>
<td>521.22</td>
<td>503.39</td>
<td>467.36</td>
<td>432.49</td>
</tr>
<tr>
<td>SD</td>
<td>142.35</td>
<td>160.73</td>
<td>139.59</td>
<td>121.77</td>
<td>112.42</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Cigarettes</th>
<th>No cigarettes</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>548.57</td>
<td>148.67</td>
<td>512.32</td>
</tr>
<tr>
<td>SD</td>
<td>148.67</td>
<td>148.67</td>
<td>136.79</td>
</tr>
</tbody>
</table>

Time to collision (TTC)

An one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cigarettes non-users and users. The means and standard deviations can be found in the table (Table 6). For non-users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 18.98$, $p = .026$), therefore degrees of freedom were corrected using Huynh-Feldt estimates of sphericity ($\varepsilon = .80$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F (3.54, 130.87) = 11.76$, $p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .47, $F (4, 34) = 9.73$, $p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p = .001$) and the 0 shields condition ($p < .001$).

Another significant effect was found between the 4 shields condition and the 0 shields condition ($p = .002$). The final significant effect was found between the 3 shields condition and the 1 shield condition ($p = .040$) and the 0 shields condition ($p = .005$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .12 for a small effect ($f = .10$), .59 for a medium effect ($f = .25$), and .96 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F (4, 116) = 7.09$, $p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .60, $F$
The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition \((p = .007)\). The other significant effect was found between the 4 shields condition and the 0 shields condition \((p = .002)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect \((f = .10)\), .66 for a medium effect \((f = .25)\), and .98 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 21), there is an increase in mean TTC when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.

![Graph of comparison of shield conditions between cigarettes users and non-users – TTC](image)

**Figure 21.** Graph of comparison of shield conditions between cigarettes users and non-users – TTC

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>5 shields</th>
<th>4 shields</th>
<th>3 shields</th>
<th>1 shield</th>
<th>0 shields</th>
</tr>
</thead>
<tbody>
<tr>
<td>M</td>
<td>.85</td>
<td>.88</td>
<td>.91</td>
<td>.97</td>
<td>1.06</td>
</tr>
<tr>
<td>SD</td>
<td>.27</td>
<td>.23</td>
<td>.25</td>
<td>.27</td>
<td>.23</td>
</tr>
<tr>
<td>Overall M</td>
<td>.83</td>
<td>.82</td>
<td>.91</td>
<td>.93</td>
<td>1.02</td>
</tr>
<tr>
<td>Overall SD</td>
<td>.24</td>
<td>.29</td>
<td>.28</td>
<td>.25</td>
<td>.28</td>
</tr>
<tr>
<td>Cigarettes M</td>
<td>.87</td>
<td>.93</td>
<td>.90</td>
<td>1.01</td>
<td>1.09</td>
</tr>
<tr>
<td>Cigarettes SD</td>
<td>.23</td>
<td>.25</td>
<td>.23</td>
<td>.20</td>
<td>.26</td>
</tr>
<tr>
<td>No cigarettes M</td>
<td>.85</td>
<td>.88</td>
<td>.91</td>
<td>.97</td>
<td>1.06</td>
</tr>
<tr>
<td>No cigarettes SD</td>
<td>.27</td>
<td>.23</td>
<td>.25</td>
<td>.28</td>
<td>.26</td>
</tr>
</tbody>
</table>

**Table 6.** Table of means and standard deviations: overall, cigarettes users and non-users - TTC

3.4.3 **Hypothesis 3C:** More recent use of cigarettes is related to higher risk-taking behavior. Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean
TTC as dependent variables. The independent variable for all three analyses was the recency of use of cigarettes; low recency users (N = 18), medium recency users (N = 1), and high recency users (N = 12).

**Distance to the closest meteor (DCM)**
An one-way ANOVA was used to compare mean DCM between low recency users (1 month or more ago, $M = 222.63$, $SD = 15.72$), medium recency users (8 days – 1 month ago, $M = 217.65$, $SD = -$) and high recency users (1 week or less ago, $M = 218.89$, $SD = 3.92$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .067$). The univariate results showed that there was no significant effect of the recency of use of cigarettes on the mean DCM ($F(2, 28) = .36$, $p = .700$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Speed**
An one-way ANOVA was used to compare mean speed between low recency users (1 month or more ago, $M = 499.23$, $SD = 119.04$), medium recency users (8 days – 1 month ago, $M = 621.29$, $SD = -$) and high recency users (1 week or less ago, $M = 499.88$, $SD = 118.92$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .917$). The univariate results showed that there was no significant effect of the recency of use of cigarettes on the mean speed ($F(2, 28) = .51$, $p = .608$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).
Time to collision (TTC)
An one-way ANOVA was used to compare mean TTC between low recency users (1 month or more ago, $M = .93, SD = .23$), medium recency users (8 days – 1 month ago, $M = .76, SD = .23$) and high recency users (1 week or less ago, $M = .93, SD = .21$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .636$). The univariate results showed that there was no significant effect of the recency of use of cigarettes on the mean TTC ($F (2, 28) = .30, p = .747$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

3.4.4 Hypothesis 3D: More frequent use of cigarettes is related to higher risk-taking behavior.
Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the frequency of use of cigarettes; low frequency users (N = 24), medium frequency users (N = 2), and high frequency users (N = 5).

Distance to the closest meteor (DCM)
An one-way ANOVA was used to compare mean DCM between low frequency users (once every 1 week or less, $M = 221.59, SD = 13.72$), medium frequency users (once every 1 week – 1 day, $M = 221.04, SD = 4.40$) and high frequency users (once every 1 day or more, $M = 218.28, SD = 4.75$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .541$). The univariate results showed that there was no significant effect of the frequency of use of cigarettes on the mean DCM ($F (2, 28) = .144, p = .867$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to
Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Speed**
An one-way ANOVA was used to compare mean speed between low frequency users (once every 1 week or less, $M = 497.16, SD = 109.54$), medium frequency users (once every 1 week – 1 day, $M = 619.95, SD = 47.67$) and high frequency users (once every 1 day or more, $M = 486.86, SD = 160.55$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .144$). The univariate results showed that there was no significant effect of the frequency of use of cigarettes on the mean speed ($F(2, 28) = 1.08, p = .353$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**
An one-way ANOVA was used to compare mean TTC between low frequency users (once every 1 week or less, $M = .93, SD = .21$), medium frequency users (once every 1 week – 1 day, $M = .71, SD = .01$) and high frequency users (once every 1 day or more, $M = .98, SD = .29$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .058$). The univariate results showed that there was no significant effect of the frequency of use of cigarettes on the mean TTC ($F(2, 28) = 1.13, p = .337$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**3.4.5 Hypothesis 3E: Usage of higher quantities of cigarettes per time is related to higher**
risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the quantity of use of cigarettes per time; low quantity users (N = 27), medium quantity users (N = 2), and high quantity users (N = 2).

**Distance to the closest meteor (DCM)**

An one-way ANOVA was used to compare mean DCM between low quantity users (2 cigarettes or less, $M = 221.32$, $SD = 13.01$), medium quantity users (2 cigarettes – 4 cigarettes, $M = 222.60$, $SD = 2.20$) and high quantity users (4 cigarettes or more, $M = 215.45$, $SD = 2.58$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .553$). The univariate results showed that there was no significant effect of the quantity of use of cigarettes per time on the mean DCM ($F (2, 28) = .22$, $p = .804$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between low quantity users (2 cigarettes or less, $M = 513.53$, $SD = 115.67$), medium quantity users (2 cigarettes – 4 cigarettes, $M = 455.40$, $SD = 185.03$) and high quantity users (4 cigarettes or more, $M = 414.97$, $SD = 75.40$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .476$). The univariate results showed that there was no significant effect of the quantity of use of cigarettes per time on the mean speed ($F (2, 28) = .83$, $p = .446$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988).
Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between low quantity users (2 cigarettes or less, \( M = .90, SD = .21 \)), medium quantity users (2 cigarettes – 4 cigarettes, \( M = 1.02, SD = .44 \)) and high quantity users (4 cigarettes or more, \( M = 1.08, SD = .19 \)). Levene’s test showed that the assumption of homogeneity of variances was met \((p = .182)\). The univariate results showed that there was no significant effect of the quantity of use of cigarettes per time on the mean TTC \((F(2, 28) = .79, p = .464)\). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .07 for a small effect \((f = .10)\), .20 for a medium effect \((f = .25)\), and .46 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

### 3.5 Hypothesis 4: Risk-taking and marijuana use

#### 3.5.1 Hypothesis 4A: Users of marijuana show more risk-taking behavior than non-users.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of marijuana; users \((N = 31)\) versus non-users \((N = 38)\).

**Distance to the closest meteor (DCM)**

An one-way ANOVA was used to compare mean DCM between users \((M = 220.95, SD = 9.70)\) and non-users \((M = 221.81, SD = 15.14)\). Levene’s test showed that the assumption of homogeneity of variances was met \((p = .356)\). The univariate results showed that there was no significant effect of whether people use marijuana or not on the mean DCM \((F(1, 67) = .08, p = .785)\). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was
.13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between users ($M = 491.12$, $SD = 109.79$) and non-users ($M = 481.06$, $SD = 117.46$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .860$). The univariate results showed that there was no significant effect of whether people use marijuana or not on the mean speed ($F(1, 67) = .13, p = .717$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between users ($M = .93$, $SD = .21$) and non-users ($M = .96$, $SD = .21$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .834$). The univariate results showed that there was no significant effect of whether people use marijuana or not on the mean TTC ($F(1, 67) = .32, p = .571$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

3.5.2 **Hypothesis 4B: Usage of marijuana influences the risk-compensation strategy.**

Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of marijuana; users (N = 31) versus non-users (N = 38) and three separate analyses were done for each group.
**Distance to the closest meteor (DCM)**

An one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both marijuana non-users and users. The means and standard deviations can be found in the table (Table 7). For non-users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 166.80, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .37$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.47, 54.23) = 13.24, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .60, $F (4, 34) = 5.66, p = .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition ($p = .001$). Another significant effect was found between the 4 shields condition and the 0 shields condition ($p = .004$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p = .003$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .038$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .10 for a small effect ($f = .10$), .39 for a medium effect ($f = .25$), and .78 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

For users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 163.71, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .30$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.19, 35.57) = 8.33, p = .005$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .57, $F (4, 27) = 5.02, p = .004$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 3 shields condition ($p = .030$) and the 1 shield condition ($p = .002$) and the 0 shields condition ($p = .028$). The other significant effect was found between the 4 shields condition and the 1 shield condition ($p = .039$) and the 0 shields condition ($p = .050$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level
used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .09 for a small effect ($f = .10$), .29 for a medium effect ($f = .25$), and .62 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 22), there is an increase in mean DCM when starting with less shields for users and non-users. However, the differences do appear to be very minimal.

![Graph of comparison of shield conditions between marijuana users and non-users – DCM](image)

**Figure 22.** Graph of comparison of shield conditions between marijuana users and non-users – DCM

<table>
<thead>
<tr>
<th>Shield</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Marijuana M</th>
<th>Marijuana SD</th>
<th>No marijuana M</th>
<th>No marijuana SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>217.38</td>
<td>7.33</td>
<td>219.96</td>
<td>13.98</td>
</tr>
<tr>
<td>4 shields</td>
<td>221.08</td>
<td>12.56</td>
<td>220.36</td>
<td>11.22</td>
<td>221.66</td>
<td>13.68</td>
</tr>
<tr>
<td>3 shields</td>
<td>223.97</td>
<td>15.95</td>
<td>225.50</td>
<td>16.01</td>
<td>222.72</td>
<td>16.01</td>
</tr>
<tr>
<td>1 shield</td>
<td>231.33</td>
<td>27.65</td>
<td>230.89</td>
<td>20.04</td>
<td>231.70</td>
<td>32.86</td>
</tr>
<tr>
<td>0 shields</td>
<td>261.89</td>
<td>71.55</td>
<td>257.68</td>
<td>69.73</td>
<td>265.33</td>
<td>73.75</td>
</tr>
</tbody>
</table>

**Speed**

An one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both marijuana non-users and users. The means and standard deviations can be found in the table (Table 8). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed ($F (4, 148)$
The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .57, \( F(4, 34) = 6.49, p = .001 \)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition \((p = .003)\) and the 0 shields condition \((p = .002)\). Another significant effect was found between the 4 shields condition and the 1 shield condition \((p = .004)\) and the 0 shields condition \((p = .001)\). The final significant effect was found between the 3 shields condition and the 1 shield condition \((p = .024)\) and the 0 shields condition \((p = .010)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect \((f = .10)\), .66 for a medium effect \((f = .25)\), and .98 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \((F(4, 120) = 9.01, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .45, \( F(4, 27) = 8.10, p < .001 \)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 0 shields condition \((p < .001)\). The next significant effect was found between the 3 shields condition and the 0 shields condition \((p = .050)\). The final significant effect was found between the 1 shield condition and the 0 shields condition \((p = .024)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .12 for a small effect \((f = .10)\), .55 for a medium effect \((f = .25)\), and .95 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 23), there is a decrease in mean speed when starting with less shields for users and non-users. However, the differences do appear to be very minimal.
Figure 23. Graph of comparison of shield conditions between marijuana users and non-users – speed

Table 8. Table of means and standard deviations: overall, marijuana users and non-users - speed

<table>
<thead>
<tr>
<th>Shield Condition</th>
<th>Overall M</th>
<th>SD</th>
<th>Marijuana M</th>
<th>SD</th>
<th>No marijuana M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>528.61</td>
<td>142.35</td>
<td>537.15</td>
<td>141.73</td>
<td>521.64</td>
<td>144.37</td>
</tr>
<tr>
<td>4 shields</td>
<td>521.22</td>
<td>160.73</td>
<td>524.95</td>
<td>160.16</td>
<td>518.18</td>
<td>163.27</td>
</tr>
<tr>
<td>3 shields</td>
<td>503.39</td>
<td>139.59</td>
<td>495.14</td>
<td>133.49</td>
<td>510.12</td>
<td>145.82</td>
</tr>
<tr>
<td>1 shield</td>
<td>467.36</td>
<td>121.77</td>
<td>490.72</td>
<td>134.56</td>
<td>448.31</td>
<td>108.35</td>
</tr>
<tr>
<td>0 shields</td>
<td>432.49</td>
<td>112.42</td>
<td>428.82</td>
<td>100.60</td>
<td>435.49</td>
<td>122.48</td>
</tr>
</tbody>
</table>

Time to collision (TTC)

An one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both marijuana non-users and users. The means and standard deviations can be found in the table (Table 9). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F$(4, 144) = 9.08, $p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .58, $F$(4, 33) = 6.56, $p = .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p = .004$) and the 0 shields condition ($p = .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .013$) and the 0 shields condition ($p = .005$). The final significant effect was found between the 3 shields condition...
and the 0 shields condition \((p = .015)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect \((f = .10)\), .66 for a medium effect \((f = .25)\), and .98 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC \((F (4, 120) = 9.44, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .47, \(F (4, 27) = 7.68, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 0 shields condition \((p = .001)\). The final significant effect was found between the 1 shield condition and the 0 shields condition \((p = .024)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .12 for a small effect \((f = .10)\), .55 for a medium effect \((f = .25)\), and .95 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 24), there is an increase in mean TTC when starting with less shields for users and non-users. However, the differences do appear to be very minimal.
3.5.3 Hypothesis 4C: More recent use of marijuana is related to higher risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the recency of use of marijuana; low recency users (N = 18), medium recency users (N = 3), and high recency users (N = 10).

Distance to the closest meteor (DCM)

An one-way ANOVA was used to compare mean DCM between low recency users (4 months or more ago, \( M = 220.96, SD = 10.43 \)), medium recency users (1 month – 4 months ago, \( M = 212.58, SD = 4.14 \)) and high recency users (1 month or less ago, \( M = 223.43, SD = 8.62 \)). Levene’s test showed that the assumption of homogeneity of variances was met (\( p = .442 \)). The univariate results showed that there was no significant effect of the recency of use.
of marijuana on the mean DCM ($F(2, 28) = 1.49, p = .242$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between low recency users (4 months or more ago, $M = 488.44, SD = 101.82$), medium recency users (1 month – 4 months ago, $M = 462.44, SD = 107.46$) and high recency users (1 month or less ago, $M = 504.55, SD = 132.44$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .501$). The univariate results showed that there was no significant effect of the recency of use of marijuana on the mean speed ($F(2, 28) = .17, p = .842$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between low recency users (4 months or more ago, $M = .94, SD = .21$), medium recency users (1 month – 4 months ago, $M = .97, SD = .20$) and high recency users (1 month or less ago, $M = .92, SD = .23$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .741$). The univariate results showed that there was no significant effect of the recency of use of marijuana on the mean TTC ($F(2, 28) = .08, p = .921$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical
power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

3.5.4 Hypothesis 4D: More frequent use of marijuana is related to higher risk-taking behavior.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the frequency of use of marijuana; low frequency users ($N = 25$), medium frequency users ($N = 5$), and high frequency users ($N = 1$).

**Distance to the closest meteor (DCM)**

An one-way ANOVA was used to compare mean DCM between low frequency users (once every 1 month or less, $M = 219.97$, $SD = 9.53$), medium frequency users (once every 1 week – 1 month, $M = 224.79$, $SD = 11.38$) and high frequency users (once every 7 days or more, $M = 226.22$, $SD = -$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .769$). The univariate results showed that there was no significant effect of the frequency of use of marijuana on the mean DCM ($F(2, 28) = .65$, $p = .529$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between low frequency users (once every 1 month or less, $M = 484.47$, $SD = 94.02$), medium frequency users (once every 1 week – 1 month, $M = 538.98$, $SD = 181.37$) and high frequency users (once every 7 days or more, $M = 418.10$, $SD = -$). Levene’s test showed that the assumption of homogeneity of variances was violated ($p = .009$). The Welch ANOVA could not be used, since at least one group had a sum of case weights of one or less than one. Therefore the one-way ANOVA
was used, keeping in mind that there was no homogeneity of variances. The univariate results showed that there was no significant effect of the frequency of use of marijuana on the mean speed \( (F(2, 28) = .65, p = .529) \). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was \( .07 \) for a small effect \( (f = .10) \), \( .20 \) for a medium effect \( (f = .25) \), and \( .46 \) for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of \( .80 \)) for a large effect, medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between low frequency users (once every 1 month or less, \( M = .93, SD = .19 \)), medium frequency users (once every 1 week – 1 month, \( M = .90, SD = .31 \)) and high frequency users (once every 7 days or more, \( M = 1.08, SD = - \)). Levene’s test showed that the assumption of homogeneity of variances was violated \( (p = .036) \). The Welch ANOVA could not be used, since at least one group had a sum of case weights of one or less than one. Therefore the one-way ANOVA was used, keeping in mind that there was no homogeneity of variances. The univariate results showed that there was no significant effect of the frequency of use of marijuana on the mean TTC \( (F(2, 28) = .30, p = .740) \). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was \( .07 \) for a small effect \( (f = .10) \), \( .20 \) for a medium effect \( (f = .25) \), and \( .46 \) for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of \( .80 \)) for a large effect, medium effect and small effect as according to Cohen (1977).

**3.5.5 Hypothesis 4E: Usage of higher quantities of marijuana per time is related to higher risk-taking behavior.**

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the quantity of use of marijuana per time; low quantity users (\( N = 30 \)), medium quantity users (\( N = 0 \)), and high quantity users (\( N = 1 \)).
Distance to the closest meteor (DCM)

An one-way ANOVA was used to compare mean DCM between low quantity users (0.6 grams or less, \( M = 220.77, SD = 9.82 \)), medium quantity users (0.6 grams – 1.0 grams, \( M = - \), \( SD = - \)) and high quantity users (1.0 grams or more, \( M = 226.22, SD = - \)). Levene’s test could not be performed since only two of the three groups were filled (low quantity users and high quantity users), and one of them only had 1 participant in it (high quantity users). Therefore an ANOVA was done, keeping in mind that there was no guarantee of homogeneity of variances. The univariate results showed that there was no significant effect of the quantity of use of marijuana per time on the mean DCM (\( F (1, 29) = .30, p = .589 \)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .07 for a small effect (\( f = .10 \)), .20 for a medium effect (\( f = .25 \)), and .46 for a large effect (\( f = .40 \)) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

Speed

An one-way ANOVA was used to compare mean speed between low quantity users (0.6 grams or less, \( M = 493.55, SD = 110.81 \)), medium quantity users (0.6 grams – 1.0 grams, \( M = -, SD = - \)) and high quantity users (1.0 grams or more, \( M = 418.10, SD = - \)). Levene’s test could not be performed since only two of the three groups were filled (low quantity users and high quantity users), and one of them only had 1 participant in it (high quantity users). Therefore an ANOVA was done, keeping in mind that there was no guarantee of homogeneity of variances. The univariate results showed that there was no significant effect of the quantity of use of marijuana per time on the mean speed (\( F (1, 29) = .45, p = .508 \)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \( p < .05 \). The post hoc analyses revealed the statistical power for this test was .07 for a small effect (\( f = .10 \)), .20 for a medium effect (\( f = .25 \)), and .46 for a large effect (\( f = .40 \)) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).
Time to collision (TTC)
An one-way ANOVA was used to compare mean TTC between low quantity users (0.6 grams or less, $M = .93, SD = .21$), medium quantity users (0.6 grams – 1.0 grams, $M = -, SD = -$) and high quantity users (1.0 grams or more, $M = 1.08, SD = -$). Levene’s test could not be performed since only two of the three groups were filled (low quantity users and high quantity users), and one of them only had 1 participant in it (high quantity users). Therefore an ANOVA was done, keeping in mind that there was no guarantee of homogeneity of variances. The univariate results showed that there was no significant effect of the quantity of use of marijuana per time on the mean TTC ($F(1, 29) = .54, p = .468$). Since this indicated that there was no significant difference between the different means, no further tests were conducted.

A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .20 for a medium effect ($f = .25$), and .46 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977).

3.6 Hypothesis 5: Risk-taking and cocaine use

3.6.1 Hypothesis 5A: Users of cocaine show more risk-taking behavior than non-users.
Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of cocaine; users (N = 6) versus non-users (N = 63).

Distance to the closest meteor (DCM)
An one-way ANOVA was used to compare mean DCM between users ($M = 222.76, SD = 8.49$) and non-users ($M = 221.29, SD = 13.28$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .662$). The univariate results showed that there was no significant effect of whether people use cocaine or not on the mean DCM ($F(1, 67) = .07, p = .793$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a
small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between users (\(M = 432.16, SD = 108.65\)) and non-users (\(M = 490.67, SD = 113.31\)). Levene’s test showed that the assumption of homogeneity of variances was met (\(p = .644\)). The univariate results showed that there was no significant effect of whether people use cocaine or not on the mean speed (\(F(1, 67) = 1.47, p = .230\)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between users (\(M = 1.06, SD = .24\)) and non-users (\(M = .94, SD = .20\)). Levene’s test showed that the assumption of homogeneity of variances was met (\(p = .826\)). The univariate results showed that there was no significant effect of whether people use cocaine or not on the mean TTC (\(F(1, 67) = 2.06, p = .156\)). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

3.6.2 **Hypothesis 5B: Usage of cocaine influences the risk-compensation strategy.**

Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of cocaine; users (\(N = \)
6) versus non-users (N = 63) and three separate analyses were done for each group.

**Distance to the closest meteor (DCM)**

An one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 10). For non-users Mauchly’s test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 287.89, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .34$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.37, 85.10) = 19.97, p < .001$). The results of the multivariate approach also showed a significant effect (Wilk's Lambda = .62, $F (4, 59) = 8.90, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p = .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .010$) and the 0 shields condition ($p < .001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .006$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .57 for a medium effect ($f = .25$), and .94 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users Mauchly’s test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 30.77, p = .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .28$). The univariate results showed that there was no significant effect of the amount of shields people started with on the mean DCM ($F (1.10, 5.50) = 1.70, p = .248$). The results of the multivariate approach also showed no significant effect (Wilk's Lambda = .42, $F (4, 2) = .70, p = .659$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .12 for a
large effect \((f = .40)\) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of \(.80)\) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 25), there is an increase in mean DCM when starting with less shields for users and non-users. However, the differences do appear to be very minimal.

![Graph](image)

**Figure 25.8.** Graph of comparison of shield conditions between cocaine users and non-users – DCM

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Cocaine M</th>
<th>Cocaine SD</th>
<th>No cocaine M</th>
<th>No cocaine SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>220.01</td>
<td>9.01</td>
<td>218.68</td>
<td>11.74</td>
</tr>
<tr>
<td>4 shields</td>
<td>221.08</td>
<td>12.56</td>
<td>223.99</td>
<td>14.13</td>
<td>220.80</td>
<td>12.49</td>
</tr>
<tr>
<td>3 shields</td>
<td>223.97</td>
<td>15.95</td>
<td>232.63</td>
<td>20.72</td>
<td>223.14</td>
<td>15.38</td>
</tr>
<tr>
<td>1 shield</td>
<td>231.33</td>
<td>27.65</td>
<td>224.58</td>
<td>5.84</td>
<td>231.98</td>
<td>28.83</td>
</tr>
<tr>
<td>0 shields</td>
<td>261.89</td>
<td>71.55</td>
<td>271.86</td>
<td>82.25</td>
<td>260.94</td>
<td>71.12</td>
</tr>
</tbody>
</table>

**Speed**

An one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 11). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \((F(4, 248)\)
The results of the multivariate approach also showed a significant effect (Wilks’ Lambda = .53, $F(4, 59) = 13.01, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p = .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .020$) and the 0 shields condition ($p < .001$). The final significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .20 for a small effect ($f = .10$), .90 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users Mauchly’s test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 28.08, p = .002$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .34$). The univariate results showed that there was no significant effect of the amount of shields people started with on the mean speed ($F(1.36, 6.81) = 2.25, p = .180$). The results of the multivariate approach also showed no significant effect (Wilks’ Lambda = .25, $F(4, 2) = 1.53, p = .431$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .13 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 26), there is a decrease in mean speed when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.
**Table 11.** Table of means and standard deviations: overall, cocaine users and non-users - speed

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>SD</th>
<th>Cocaine M</th>
<th>SD</th>
<th>No cocaine M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>528.61</td>
<td>142.35</td>
<td>465.16</td>
<td>164.28</td>
<td>534.65</td>
<td>140.07</td>
</tr>
<tr>
<td>4 shields</td>
<td>521.22</td>
<td>160.73</td>
<td>505.48</td>
<td>200.25</td>
<td>522.72</td>
<td>158.34</td>
</tr>
<tr>
<td>3 shields</td>
<td>503.39</td>
<td>139.59</td>
<td>400.50</td>
<td>85.89</td>
<td>513.19</td>
<td>140.20</td>
</tr>
<tr>
<td>1 shield</td>
<td>467.36</td>
<td>121.77</td>
<td>398.01</td>
<td>122.17</td>
<td>473.97</td>
<td>120.62</td>
</tr>
<tr>
<td>0 shields</td>
<td>432.49</td>
<td>112.42</td>
<td>403.32</td>
<td>103.36</td>
<td>435.27</td>
<td>113.63</td>
</tr>
</tbody>
</table>

**Time to collision (TTC)**

An one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 12). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F(4, 244) = 17.15, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .51, $F(4, 58) = 6.56, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 0 shields condition ($p < .001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p <
The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .013$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .20 for a small effect ($f = .10$), .90 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 18.69, p = .045$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .33$). The univariate results showed that there was no significant effect of the amount of shields people started with on the mean TTC ($F (1.31, 6.55) = 1.84, p = .226$). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .22, $F (4, 2) = 1.75, p = .396$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .13 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 27J0), there is an increase in mean TTC when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.

![Graph of comparison of shield conditions between cocaine users and non-users – TTC](image)

*Figure 27J0. Graph of comparison of shield conditions between cocaine users and non-users – TTC*
Table 12. Table of means and standard deviations: overall, cocaine users and non-users - TTC

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Cocaine</th>
<th>No cocaine</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>5 shields</td>
<td>.85</td>
<td>.27</td>
<td>1.01</td>
</tr>
<tr>
<td>4 shields</td>
<td>.88</td>
<td>.23</td>
<td>.92</td>
</tr>
<tr>
<td>3 shields</td>
<td>.91</td>
<td>.25</td>
<td>1.13</td>
</tr>
<tr>
<td>1 shield</td>
<td>.97</td>
<td>.27</td>
<td>1.19</td>
</tr>
<tr>
<td>0 shields</td>
<td>1.06</td>
<td>.23</td>
<td>1.14</td>
</tr>
</tbody>
</table>

3.7 Hypothesis 6: Risk-taking and ecstasy use

3.7.1 Hypothesis 6A: Users of ecstasy show more risk-taking behavior than non-users.

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of ecstasy; users (N = 11) versus non-users (N = 58).

Distance to the closest meteor (DCM)

An one-way ANOVA was used to compare mean DCM between users (M = 219.91, SD = 7.23) and non-users (M = 221.71, SD = 13.74). Levene’s test showed that the assumption of homogeneity of variances was met (p = .275). The univariate results showed that there was no significant effect of whether people use ecstasy or not on the mean DCM (F (1, 67) = .18, p = .675). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was p < .05. The post hoc analyses revealed the statistical power for this test was .13 for a small effect (f = .10), .53 for a medium effect (f = .25), and .91 for a large effect (f = .40) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

Speed

An one-way ANOVA was used to compare mean speed between users (M = 468.55, SD = 109.88) and non-users (M = 488.81, SD = 114.65). Levene’s test showed that the assumption of homogeneity of variances was met (p = .797). The univariate results showed that there was no significant effect of whether people use ecstasy or not on the mean speed (F (1, 67) = .29, p = .590). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted.
using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between users ($M = .99$, $SD = .21$) and non-users ($M = .94$, $SD = .20$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .944$). The univariate results showed that there was no significant effect of whether people use ecstasy or not on the mean TTC ($F(1, 67) = .46$, $p = .499$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**3.7.2 Hypothesis 6B: Usage of ecstasy influences the risk-compensation strategy.**

Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of ecstasy; users ($N = 11$) versus non-users ($N = 58$) and three separate analyses were done for each group.

**Distance to the closest meteor (DCM)**

An one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 13). For non-users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 265.02, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .34$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.37, 78.26) = 19.83, p < .001$). The results of the multivariate approach also
showed a significant effect (Wilks' Lambda = .61, \(F (4, 54) = 8.54, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition \((p = .003)\) and the 0 shields condition \((p < .001)\).

Another significant effect was found between the 4 shields condition and the 1 shield condition \((p = .023)\) and the 0 shields condition \((p < .001)\). The next significant effect was found between the 3 shields condition and the 0 shields condition \((p < .001)\). The final significant effect was found between the 1 shield condition and the 0 shields condition \((p = .006)\). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .13 for a small effect \((f = .10)\), .54 for a medium effect \((f = .25)\), and .92 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

For users, Mauchly's test indicated that the assumption of sphericity had been violated \((\chi^2 (9) = 58.59, p < .001)\), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity \((\varepsilon = .29)\). The univariate results showed that there was no significant effect of the amount of shields people started with on the mean DCM \((F (1.15, 11.51) = 1.98, p = .187)\). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .56, \(F (4, 7) = 1.39, p = .331\)). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was \(p < .05\). The post hoc analyses revealed the statistical power for this test was .06 for a small effect \((f = .10)\), .12 for a medium effect \((f = .25)\), and .22 for a large effect \((f = .40)\) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 28), there is an increase in mean DCM when starting with less shields for users and non-users. However, the differences do appear to be very minimal.
Figure 28. Graph of comparison of shield conditions between ecstasy users and non-users – DCM

Table 13. Table of means and standard deviations: overall, ecstasy users and non-users - DCM

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Ecstasy M</th>
<th>Ecstasy SD</th>
<th>No ecstasy M</th>
<th>No ecstasy SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>217.58</td>
<td>7.12</td>
<td>219.03</td>
<td>12.16</td>
</tr>
<tr>
<td>4 shields</td>
<td>221.08</td>
<td>12.56</td>
<td>219.37</td>
<td>11.45</td>
<td>221.40</td>
<td>12.83</td>
</tr>
<tr>
<td>3 shields</td>
<td>223.97</td>
<td>15.95</td>
<td>227.01</td>
<td>17.29</td>
<td>223.39</td>
<td>15.78</td>
</tr>
<tr>
<td>1 shield</td>
<td>231.33</td>
<td>27.65</td>
<td>224.84</td>
<td>10.29</td>
<td>232.57</td>
<td>29.73</td>
</tr>
<tr>
<td>0 shields</td>
<td>261.89</td>
<td>71.55</td>
<td>249.86</td>
<td>63.84</td>
<td>264.17</td>
<td>73.20</td>
</tr>
</tbody>
</table>

Speed

An one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 14). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed \((F(4, 228) = 14.82, p < .001)\). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .55, \(F(4, 54) = 11.17, p < .001\)). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition \((p = .001)\) and the 0 shields condition \((p < .001)\). Another significant effect was found between the 4 shields condition and the 1 shield condition \((p = .007)\) and the 0 shields condition \((p < .001)\). The final significant effect was found between the 3 shields condition and the 0 shields condition \((p < .001)\). A post hoc power analysis was conducted using the
software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .19 for a small effect ($f = .10$), .87 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed ($F (4, 40) = 2.61, p = .049$). The results of the multivariate approach showed no significant effect (Wilks' Lambda = .53, $F (4, 7) = 1.53, p = .293$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small effect ($f = .10$), .19 for a medium effect ($f = .25$), and .45 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 29), there is an increase in mean speed when starting with less shields for users and non-users. However, the differences do appear to be very minimal.

![Graph](image)

*Figure 29*. Graph of comparison of shield conditions between ecstasy users and non-users – speed

<table>
<thead>
<tr>
<th>Table 14. Table of means and standard deviations: overall, ecstasy users and non-users – speed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
</tr>
<tr>
<td>Mean speed</td>
</tr>
</tbody>
</table>
Time to collision (TTC)

An one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for both cocaine non-users and users. The means and standard deviations can be found in the table (Table 15). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F(4, 224) = 14.89, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .53, $F(4, 53) = 11.82, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .021$) and the 0 shields condition ($p < .001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .19 for a small effect ($f = .10$), .87 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users the univariate results showed that there was no significant effect of the amount of shields people started with on the mean TTC ($F(4, 40) = 2.50, p = .057$). The results of the multivariate approach also showed no significant effect (Wilks' Lambda = .56, $F(4, 7) = 1.37, p = .336$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .07 for a small
effect \( (f = .10) \), .19 for a medium effect \( (f = .25) \), and .45 for a large effect \( (f = .40) \) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 30), there is an increase in mean TTC when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.

![Graph of comparison of shield conditions between ecstasy users and non-users – TTC](image)

*Figure 3012. Graph of comparison of shield conditions between ecstasy users and non-users – TTC*

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>Overall SD</th>
<th>Ecstasy M</th>
<th>Ecstasy SD</th>
<th>No ecstasy M</th>
<th>No ecstasy SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
<td>.85</td>
<td>.27</td>
<td>.91</td>
<td>.29</td>
<td>.84</td>
<td>.22</td>
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<tr>
<td>4 shields</td>
<td>.88</td>
<td>.23</td>
<td>.91</td>
<td>.30</td>
<td>.88</td>
<td>.27</td>
</tr>
<tr>
<td>3 shields</td>
<td>.91</td>
<td>.25</td>
<td>.98</td>
<td>.27</td>
<td>.89</td>
<td>.25</td>
</tr>
<tr>
<td>1 shield</td>
<td>.97</td>
<td>.27</td>
<td>1.03</td>
<td>.29</td>
<td>.97</td>
<td>.21</td>
</tr>
<tr>
<td>0 shields</td>
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<td>.23</td>
<td>1.13</td>
<td>.29</td>
<td>1.05</td>
<td>.26</td>
</tr>
</tbody>
</table>

**3.8 Hypothesis 7: Risk-taking and amphetamine use**

**3.8.1 Hypothesis 7A: Users of amphetamine show more risk-taking behavior than non-users.**

Three one-way ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The independent variable for all three analyses was the usage of amphetamine; users (N = 4) versus non-users (N = 65).

Distance to the closest meteor (DCM)
An one-way ANOVA was used to compare mean DCM between users ($M = 221.60, SD = 8.52$) and non-users ($M = 221.41, SD = 13.17$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .628$). The univariate results showed that there was no significant effect of whether people use amphetamine or not on the mean DCM ($F (1, 67) < .01, p = .977$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Speed**

An one-way ANOVA was used to compare mean speed between users ($M = 470.38, SD = 136.13$) and non-users ($M = 486.52, SD = 113.00$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .996$). The univariate results showed that there was no significant effect of whether people use amphetamine or not on the mean speed ($F (1, 67) = .08, p = .785$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

**Time to collision (TTC)**

An one-way ANOVA was used to compare mean TTC between users ($M = 1.02, SD = .26$) and non-users ($M = .94, SD = .20$). Levene’s test showed that the assumption of homogeneity of variances was met ($p = .705$). The univariate results showed that there was no significant effect of whether people use amphetamine or not on the mean TTC ($F (1, 67) = .50, p = .483$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the
analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was 
.13 for a small effect ($f = .10$), .53 for a medium effect ($f = .25$), and .91 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).

3.8.2 Hypothesis 7B: Usage of amphetamine influences the risk-compensation strategy.
Six repeated measures ANOVA’s were used. They used the mean DCM, mean speed and mean TTC as dependent variables. The file was split based on usage of amphetamine; users (N = 4) versus non-users (N = 65) and three separate analyses were done for each group.

Distance to the closest meteor (DCM)
A one-way repeated measures ANOVA was used to compare mean DCM between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for amphetamine non-users and the Friedman test was used for amphetamine users. The means and standard deviations can be found in the table (Table 16). For non-users Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2 (9) = 300.577, p < .001$), therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = .34$). The univariate results showed that there was a significant effect of the amount of shields people started with on the mean DCM ($F (1.35, 86.11) = 22.17, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .61, $F (4, 61) = 9.87, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 3 shields condition ($p = .030$) and the 1 shield condition ($p = .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .013$) and the 0 shields condition ($p < .001$). The next significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .002$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .14 for a small effect ($f = .10$), .59 for a medium effect ($f = .25$), and .94 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect, but not a medium effect and small effect as according to Cohen (1977).
For users the Friedman test showed no significant effect of different shield conditions on DCM ($\chi^2(4) = .600, p = .963$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .13 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 31), there is an increase in mean DCM when starting with less shields for users and less strongly so for non-users. The differences appear to be very minimal.

Figure 31. Graph of comparison of shield conditions between amphetamine users and non-users – DCM

Table 16. Table of means and standard deviations: overall, amphetamine users and non-users – DCM

<table>
<thead>
<tr>
<th>Shield Condition</th>
<th>Overall</th>
<th>Amphetamine</th>
<th>No amphetamine</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
<td>M</td>
</tr>
<tr>
<td>5 shields</td>
<td>218.80</td>
<td>11.48</td>
<td>221.02</td>
</tr>
<tr>
<td>4 shields</td>
<td>221.08</td>
<td>12.56</td>
<td>223.60</td>
</tr>
<tr>
<td>3 shields</td>
<td>223.97</td>
<td>15.95</td>
<td>224.40</td>
</tr>
<tr>
<td>1 shield</td>
<td>231.33</td>
<td>27.65</td>
<td>229.47</td>
</tr>
<tr>
<td>0 shields</td>
<td>261.89</td>
<td>71.55</td>
<td>222.90</td>
</tr>
</tbody>
</table>

Speed

A one-way repeated measures ANOVA was used to compare mean speed between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3
shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for amphetamine non-users and the Friedman test was used for amphetamine users. The means and standard deviations can be found in the table (Table 17). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean speed ($F(4, 256) = 16.78, p < .001$). The results of the multivariate approach also showed a significant effect (Wilks' Lambda = .54, $F(4, 61) = 13.24, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .005$) and the 0 shields condition ($p < .001$). The final significant effect was found between the 3 shields condition and the 0 shields condition ($p < .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .21 for a small effect ($f = .10$), .91 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users the Friedman test showed no significant effect of different shield conditions on DCM ($\chi^2(4) = .211, p = .995$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .13 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 32), there is a decrease in mean speed when starting with less shields for users and non-users. The differences appear to be small.
Figure 32. Graph of comparison of shield conditions between amphetamine users and non-users – speed

Table 17. Table of means and standard deviations: overall, amphetamine users and non-users – speed

<table>
<thead>
<tr>
<th>Shield condition</th>
<th>Overall M</th>
<th>SD</th>
<th>Amphetamine M</th>
<th>SD</th>
<th>No amphetamine M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 shields</td>
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<td>142.35</td>
<td>540.34</td>
<td>199.16</td>
<td>527.89</td>
<td>140.21</td>
</tr>
<tr>
<td>4 shields</td>
<td>521.22</td>
<td>160.73</td>
<td>545.69</td>
<td>193.83</td>
<td>519.72</td>
<td>160.15</td>
</tr>
<tr>
<td>3 shields</td>
<td>503.39</td>
<td>139.59</td>
<td>488.81</td>
<td>176.16</td>
<td>504.29</td>
<td>138.70</td>
</tr>
<tr>
<td>1 shield</td>
<td>467.36</td>
<td>121.77</td>
<td>491.19</td>
<td>248.58</td>
<td>465.89</td>
<td>113.22</td>
</tr>
<tr>
<td>0 shields</td>
<td>432.49</td>
<td>112.42</td>
<td>428.35</td>
<td>79.12</td>
<td>432.75</td>
<td>114.61</td>
</tr>
</tbody>
</table>

Time to collision (TTC)

A one-way repeated measures ANOVA was used to compare mean TTC between shield condition 5 (5 shields at start), shield condition 4 (4 shields at start), shield condition 3 (3 shields at start), shield condition 1 (1 shield at start), and shield condition 0 (0 shields at start) for amphetamine non-users and the Friedman test was used for amphetamine users. The means and standard deviations can be found in the table (Table 18). For non-users the univariate results showed that there was a significant effect of the amount of shields people started with on the mean TTC ($F(4, 252) = 17.06, p < .001$). The results of the multivariate approach also showed a significant effect ($\text{Wilks' Lambda} = .52, F(4, 60) = 14.14, p < .001$). The post-hoc Bonferroni pairwise comparisons showed significant differences between the 5 shields condition and the 1 shield condition ($p < .001$) and the 0 shields condition ($p < .001$). Another significant effect was found between the 4 shields condition and the 1 shield condition ($p = .017$) and the 0 shields condition ($p < .001$). The next significant effect was
found between the 3 shields condition and the 0 shields condition ($p = .022$). The final significant effect was found between the 1 shield condition and the 0 shields condition ($p = .001$). A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .21 for a small effect ($f = .10$), .91 for a medium effect ($f = .25$), and 1 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was adequate power (i.e., power of .80) for a large effect and medium effect, but not a small effect as according to Cohen (1977).

For users the Friedman test showed no significant effect of different shield conditions on DCM ($\chi^2 (4) = 2.600, p = .627$). Since this indicated that there was no significant difference between the different means, no further tests were conducted. A post hoc power analysis was conducted using the software package, GPower (Faul & Erdfelder, 1992). The alpha level used for the analysis was $p < .05$. The post hoc analyses revealed the statistical power for this test was .05 for a small effect ($f = .10$), .08 for a medium effect ($f = .25$), and .13 for a large effect ($f = .40$) as according to Cohen (1988). Thus, there was inadequate power (i.e., power of .80) for a large effect, medium effect and small effect as according to Cohen (1977). As can be seen in the graph (Figure 33), there is an increase in mean TTC when starting with less shields for users and non-users. There is a clear difference between the users and the non-users.

![Figure 33](#)

*Figure 33. Graph of comparison of shield conditions between amphetamine users and non-users – TTC*

*Table 18. Table of means and standard deviations: overall, amphetamine users and non-users – TTC*

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Amphetamine</th>
<th>No amphetamine</th>
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<tr>
<td>Mean TTC</td>
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<td>5</td>
<td></td>
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</tbody>
</table>
In sum, several results were found regarding the risk-taking behavior of participants in the current study. Some results showed the expected trends, whereas others did not. Several issues regarding the power of some tests were found, especially for reliably detecting small and medium effects. The following section will discuss the results in more detail.

4. Discussion

4.1 Hypothesis 1: Risk homeostasis

Comparison of shield conditions

Significant differences between the different shield conditions (5, 4, 3, 1 and 0 shields) were found for all three risk behavior variables (DCM, speed and TTC). An increase of shields given in a condition was related to an increase in speed and a decrease in DCM and TTC. These findings support the risk homeostasis theory, since the noticeable increase of protective measures led to participants showing more risk-taking behavior by increasing their speed, decreasing the distance they kept to meteors and decreasing their TTC.

Comparison of shields left within shield conditions

No significant differences were found for DCM within the conditions. Significant differences in speed were found in each condition and some significant effects were found for TTC (only within the 5 shields condition). All significant effects were seemingly contradictory to the hypothesis and the risk homeostasis theory, since a decrease in the amount of shields actually led to an increase in speed and a decrease in TTC.

Risk homeostasis theory

The results from the tests yielded evidence supporting the risk homeostasis theory. The long-term effect of awareness of protective measures on risk-taking behavior was clearly found and the significant findings that seemingly contradicted the risk homeostasis theory were only a few and all concerned the more short-term effects. This fits perfectly with the model by Wilde (1982), in which he suggests that risk compensation is subject to lagged feedback.
and the effect it has on risk-taking behavior is more long-term than short-term. Due to the only manipulation being a difference in shields and the randomization of the order participants did sessions in, it is fairly certain that the effect was caused by a change in the desired adjustment behavior of participants. The randomization should have helped negate any learning effects or changes in skill, but the manipulation of a difference in shields in each session should have still had an effect on the perceived risk level and thus cause people to take more risk when more protective measures were in place to get closer to their target risk level. This is exactly what was observed when lagged feedback from the model (Wilde, 1982) was taken into account.

4.2 Hypotheses 2A, 2B, 2C, 2D and 2E: Alcohol use

Hypothesis 2A: Users of alcohol show more risk-taking behavior than non-users.
No significant effects of being a user- or a non-user of alcohol on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. For TTC, users were found to score quite a bit lower than non-users. However, this effect was not significant.

These findings are surprising when considering the body of research on alcohol use and risk-taking, which generally indicates that alcohol use is related to increased risk-taking (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Schwarz, Burkhart & Green, 1978; Weaver, Milich & Fillmore, 2011). One of the likely causes of the inconclusive results was the small size of the non-users group (N = 5) and general small sample size. This caused the tests that were used to have a too low power (< .80) to reliably find a small effect and medium effect. A larger sample size would have led to more conclusive results. However, a larger sample that also includes enough non-users might be difficult to obtain, since most adults in the Netherlands drink alcohol (Van Laar et al., 2016).

Hypothesis 2B: Usage of alcohol influences the risk compensation strategy.
Users of alcohol showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. Non-users of alcohol also showed an increase of risk-taking behavior across all three variables when the amount of shields given in a condition was increased. However, the effect was only found to be significant for speed and could only be called a trend (p ≤ 0.10) for DCM and TTC. One of the causes was the small size of the non-users group (N = 5). The power on the tests finding trends for non-users was not at a
sufficient height of at least .80 for reliably detecting a large effect, medium effect and small effect. It thus seems very likely that a larger sample size would have led to more conclusive results. This might however be difficult to obtain, since most adults in the Netherlands drink alcohol (Van Laar et al., 2016).

Interestingly, non-users showed less risk-taking behavior as compared to users when they were given a low amount of shields for the variables of speed and TTC. It can be concluded that both users and non-users show risk compensation, but the trend indicates that non-users could possibly show slightly larger risk compensation when it comes to situations with less protective measures in place. This is interesting, since it could mean that alcohol users might act more risky in situations where they know they are not protected as compared to non-users. A practical example might for example be driving around with no seatbelts on. When non-users would be aware of driving without a seatbelt, they would strongly compensate, whereas it is possible that users would not compensate as much and endanger their lives and possibly the lives of others. Similar risky behavior could be seen, for example, during work at an industrial site where the protective measures are failing. This could certainly be seen as a benefit of employing someone who abstains from alcohol, as they would react more appropriately to a perceived lack of safety measures. As mentioned, the effect was only found for speed and found as a trend for DCM and TTC, and was found using a small sample size with low power for non-users. Future research with a larger sample size should help to get a more accurate picture of the difference between alcohol users and non-users.

Hypothesis 2C: More recent use of alcohol is related to higher risk-taking behavior.

No significant effects of recency of use of alcohol on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. A possible explanation of this result could be that drinking reasonably regularly is seen as fairly normal within the Netherlands. As discussed before, most people in the Netherlands do drink (Van Laar et al., 2016). It might thus not be perceived as all too risky to have a drink every now and then as long as one does not consume large amounts. The other issue was the groups being too small. The tests that were done were all only able to reach a desired power of .80 for reliably detecting a large effect, but not a small and medium effect. Similar tests with larger groups for a more conclusive result would therefore be interesting. It could also be the case that a country where alcohol use is less normal, or even somewhat frowned upon, as compared to the
Netherlands might show more of an effect of recency of alcohol use on risk-taking behavior in future studies.

**Hypothesis 2D: More frequent use of alcohol is related to higher risk-taking behavior.**

No significant effects of frequency of use of alcohol on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. This contradicts the findings regarding this topic that were discussed in the introduction (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011). The assumption is that this contradicting finding might be explained by the relatively small size of the low frequency user group (N = 12) and general small sample size, since the power of all the tests was only able to reach the desired .80 for reliably detecting a large effect, and not a medium effect and small effect. A larger sample size would have led to more conclusive results.

This is important to look into in future research. A similar study with larger groups might very well find the same contradicting findings that were found here, but with a large enough power of their tests. In that case there would be a lot stronger evidence supporting that there might not be an effect in a setting like this one. This could lead to more detailed research into the exact effects of frequency of alcohol use on risk-taking behavior and in which settings risk-taking behavior is and is not influenced.

**Hypothesis 2E: Usage of higher quantities of alcohol per time is related to higher risk-taking behavior.**

No significant effects of quantity of alcohol used per time on risk-taking behavior were found. However, a trend of change of risk-taking behavior when higher amounts of alcohol were used per time was found for speed (p = .079) and a similar effect approaching significance (p = .127) was found for TTC. If a larger sample size was used, significant effects would have likely been found. Especially the high quantity user group was small in this study (N = 7) and the general sample size was also not very large. This led to issues with the power of the tests used, which was only able to reach the desired .80 for reliably detecting a large effect and not a small effect and medium effect. This may explain why the data did not simply show a significant effect for increase of risk-taking behavior with higher alcohol consumption per time.

The small size of the high quantity user group and general small sample size may have led to an inaccurate assessment of the speed and TTC people in this user group would generally display, as reflected by the low power of the tests. Thus, these findings do not
seem to truly contradict the findings discussed in the introduction (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011). In conclusion the results seem to show some support for this hypothesis, but do need to be further tested using a larger sample size in future studies.

4.3 Hypotheses 3A, 3B, 3C, 3D and 3E: Cigarettes use

Hypothesis 3A: Users of cigarettes show more risk-taking behavior than non-users. No significant effects of being a user or a non-user of cigarettes on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. This contradicts the findings of Lejuez et al. (2003) regarding this topic that were discussed in the introduction. This may have been caused by the difference in the tests used in their study and this one.

It is however important to note that for speed users did averagely score higher than non-users and for TTC they scored lower than non-users. The users and non-users did at least show the expected differences, although the effects were not significant. The power of all the tests was also found to be rather low, and only able to reach the desired power of .80 for reliably detecting a large effect and not a small effect or medium effect. A larger sample size in future studies could help remedy this issue, and determine whether the differences found here are significant when groups are made large enough to raise the power to a minimum of .80 for even a small effect (f = .10). This author theorizes that the link between cigarettes use and increased risk-taking behavior will likely be found in such future studies.

Hypothesis 3B: Usage of cigarettes influences the risk compensation strategy.
Both users and non-users of cigarettes showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. Non-users showed less risk-taking behavior in general as compared to the users for speed and TTC. Both groups showed a similar trend of increase of risk-taking behavior when more shields were given, but the risk-taking behavior of the non-users was found to consistently stay below that of the users.

This author theorizes that this general trend of users of cigarettes behaving a bit more risky regardless of the protective measures could be related to the negative media attention about smoking and the warning on packages of cigarettes in the Netherlands. Most smokers are aware of the dangers, and decide to smoke anyway. They might just have a slightly higher target risk level than the non-users do and therefore compensate for risk a little less than non-users. This was also seen in the non-significant effects found for hypothesis 3A.
Although no significant effect was found there, it also showed a trend towards slightly more risk-taking behavior for users of cigarettes as compared to non-users.

**Hypothesis 3C: More recent use of cigarettes is related to higher risk-taking behavior.**

No significant effects of recency of use of cigarettes on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small size of the medium recency user group (N = 1) and the general sample size. This led to a very low power on all the tests done for this user group, and the tests all not reaching the desired power of .80 to find a small effect, medium effect and large effect. A larger sample size would therefore have helped lead to more conclusive results.

However, this author theorizes that, since most people do not know of an effect on health of recency of use, people having smoked more recently might not necessarily be feeling like they are risking more. Therefore, even if it is riskier, it would perhaps not correlate to more risk-taking behavior in other domains. This might be different when it concerns a difference in recency of use between someone who quit a while ago and someone who is still actively smoking, as people do often hear how quitting at any time can still lead to improvements of their health later on. It could thus be interesting to also look at the difference between people who recently quit using cigarettes and active users in future studies.

**Hypothesis 3D: More frequent use of cigarettes is related to higher risk-taking behavior.**

No significant effects of frequency of use of cigarettes on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small sizes of the medium frequency user group (N = 2) and the high frequency user group (N = 5) and the general sample size. This led to quite low power on all of the tests, and none of the test reached the desired power of .80 for reliably detecting a small effect, medium effect and large effect. A larger sample size would have led to more conclusive results.

This author theorizes that once a larger sample size is used a significant effect could very well be found, since most people are aware of the dangers of use of cigarettes and yet knowingly use them more often. Thus, the situation is very similar to that of users of alcohol, where earlier research did show an effect of frequency of use (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011).
Hypothesis 3E: Usage of higher quantities of cigarettes per time is related to higher risk-taking behavior.

No significant effects of quantity of use of cigarettes per time on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small sizes of the medium quantity user group (N = 2) and the high quantity user group (N = 2) and the general sample size. The power of the tests was too low to reach the desired .80 power to find a small effect, medium effect and large effect. This was an issue, and a larger sample size would have led to more conclusive results.

This author theorizes that once a larger sample size is used a significant effect could very well be found. This again relates to the risk smokers knowingly take, and the thus seemingly higher risk of using large amounts of cigarettes whenever one uses them. Thus, there is similarity to the situation of users of alcohol, where earlier research did show an effect of quantity of use (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011).

4.4 Hypotheses 4A, 4B, 4C, 4D and 4E: Marijuana use

Hypothesis 4A: Users of marijuana show more risk-taking behavior than non-users.
No significant effects of being a user or a non-user of marijuana on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. This contradicts the findings regarding this topic that were discussed in the introduction (Hanson, Thayer & Tapert, 2014). However, for speed users did averagely score higher than non-users and for TTC they scored lower than non-users. The users and non-users did at least show the expected differences, although the effects were not significant. The power of the tests that were done again was very low, and only able to reach the desired .80 power for reliably detecting a large effect, and not a small effect and medium effect. It is thus possible that research with a larger sample size might find significant results, or at the very least more conclusive results.

This author theorizes that, since people never hear about deaths due to use of marijuana and the substance is legal in the Netherlands; people might very well not be consciously taking that much of a risk when using marijuana in the Netherlands. Therefore, more interesting than just increasing the sample size used could be to also do the test in a country where marijuana is illegal. This could very well lead to a completely different outcome, since illegal actions carry more risk and therefore might be taken more by individuals who are more prone to show risk-taking behavior.
Hypothesis 4B: Usage of marijuana influences the risk compensation strategy.
Both users and non-users of marijuana showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. However, the differences in risk compensation between the two groups were minimal. Thus, no evidence was found to support this hypothesis.

This author maintains that the relatively low risk of using marijuana that the public is aware of and the legality of the substance in the Netherlands might have caused the absence of a significant effect being found in this study. This effect should therefore be studied again in a country where marijuana is illegal.

Hypothesis 4C: More recent use of marijuana is related to higher risk-taking behavior.
No significant effects of recency of use of marijuana on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small size of the medium recency user group (N = 3), the general sample size and to a lesser extent the size of the high recency group (N = 10). This caused the power of the tests done to be below the desired .80 for reliably detecting a large effect, medium effect and small effect.

A larger sample size would have led to more conclusive results, although some differences were rather small and might thus need quite large groups to be found to be significant. Furthermore, the location of the research of the Netherlands might have also played a role here again. This effect, like the others, should be studied again in a country where marijuana is illegal.

Hypothesis 4D: More frequent use of marijuana is related to higher risk-taking behavior.
No significant effects of frequency of use of marijuana on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small sizes of the medium frequency user group (N = 5) and the high frequency user group (N = 1). The power of all tests again was too low, and did not reach the desired power of .80 for finding a large effect, medium effect and small effect. Differences between groups were fairly small, except for the high frequency user group. However, since this group consisted of only one participant, it is hard to say whether this group was representative of the same group in society.

A larger sample size would have led to more conclusive results. The study taking place in the Netherlands might have contributed to the absence of a significant effect being
found in this study for this effect as well. This effect should, like the others, not only be
studied with a larger sample size, but also in a country where marijuana is illegal.

*Hypothesis 4E: Usage of higher quantities of marijuana per time is related to higher risk-
taking behavior.*

No significant effects of quantity of use of marijuana per time on risk-taking behavior were
found. Thus, no evidence was found to support this hypothesis. The main cause in this case
was the non-existence of the medium quantity user group (N = 0) and the small size of the
high quantity user group (N = 1), and the general sample size. In this case it made it hard to
say much about the data. The power of the tests done here was again found to be too low
(below .80) to reliably detect a large effect, medium effect and small effect.

A larger sample size is certainly necessary to take another look at this effect and
would lead to more conclusive results. The location of the Netherlands might, like with the
other effects regarding marijuana use, contribute to the absence of a significant effect being
found in future studies. Thus, besides increasing the sample size of the groups, future studies
into this effect should also be done in a country where marijuana is illegal.

4.5 *Hypothesis 5A and 5B: Cocaine use*

**Hypothesis 5A: Users of cocaine show more risk-taking behavior than non-users.**

No significant effects of being a user or a non-user of cocaine on risk-taking behavior were
found. Thus, no evidence was found to support this hypothesis. One of the causes was the
small size of the users group (N = 6) and the general sample size. The power tests showed
that power on the tests used only reached the desired .80 for reliably detecting a large effect,
and could not reliably detect a small effect and medium effect. Thus, a larger sample size
would have led to more conclusive results.

Interestingly, non-users scored higher for risk-taking behavior than users, even
though this difference was not significant. The data pointed in the opposite direction of the
hypothesis. This was surprising, considering the research discussed regarding increased risk-
taking behavior amongst users of illegal substances (Centers for Disease Control and
Prevention, 1999; Chitwood et al., 2000; Friedman, 1998; Joe & Simpson, 1995; Kral,
Bluthenthal, Booth, & Watters, 1998; Murray et al., 2003; Rhodes et al., 1990). It is possible
that the effect would be found as expected if another study would use a larger sample size to
get the required power to find the effect. An alternative explanation for the result could be
that the demographic used here consisting of mostly young adult university students might
show a different effect of cocaine use on risk-taking behavior than the average population.

**Hypothesis 5B: Usage of cocaine influences the risk compensation strategy.**
Non-users of cocaine showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. Users of cocaine also showed an increase of risk-taking behavior across all three variables when the amount of shields given in a condition was increased. However, the effect was not significant for any of the variables for users. One of the causes was the small size of the users group (N = 6). The power of all tests for users showed that the power was far below the desired .80 for finding a small effect, medium effect and large effect. Thus, no effect could reliably be found for this group. A larger sample size would have led to more conclusive results.

Interestingly, the results for users did show a difference in risk compensation compared to non-users for speed and TTC, even though it was not significant. The data seems to indicate that the general level of risk-taking behavior is lower for users than non-users, and that users more quickly start compensating with safer behavior when situations get riskier compared to non-users. However, these results are all not significant and based on a sample of only 6 cocaine users. It is possible that the effect would be different if another study would use a larger sample size. The differences between the two groups were fairly large, and if they would be found again with larger groups and higher power on tests in future studies, an alternative explanation for the result could be the used demographic. The demographic consisted of mostly young adult university students, which might have influenced the effect of cocaine use on risk compensation strategies in a way that was not foreseen in the current study. Future studies could not only use a larger sample size, but also a sample that includes participants from several different environments, and is not mostly made up out of young adult university students.

**4.6 Hypothesis 6A and 6B: Ecstasy use**

**Hypothesis 6A: Users of ecstasy show more risk-taking behavior than non-users.**
No significant effects of being a user or a non-user of ecstasy on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the relatively small size of the users group (N = 11). The power of the used tests was only able to reach the desired .80 for reliably detecting a large effect, and not a medium effect and small effect. Thus, a larger sample size would have led to more conclusive results.
Interestingly, non-users scored higher for risk-taking behavior than users, even though this difference was not significant. The data pointed in the opposite direction of the hypothesis. This was surprising, considering the research discussed regarding increased risk-taking behavior amongst users of illegal substances (Centers for Disease Control and Prevention, 1999; Chitwood et al., 2000; Friedman, 1998; Joe & Simpson, 1995; Kral, Bluthenthal, Booth, & Watters, 1998; Murray et al., 2003; Rhodes et al., 1990). It is possible that the effect would be found as expected if another study would use a larger sample size, giving their study more power for their tests. The alternative explanation for the result could be that the demographic used here consisting of mostly young adult university students might show a different link between ecstasy use on risk-taking behavior than the average population. Future studies using larger and different samples consisting of a group of participants that is more representative of the general population could check if the insignificant effect that was found here would be found in those samples as well and be significant in their study, or whether the effect is different than what was found here and more along the lines of what was expected in this study.

_Hypothesis 6B: Usage of ecstasy influences the risk compensation strategy._
Non-users of ecstasy showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. Users of ecstasy also showed an increase of risk-taking behavior across all three variables when the amount of shields given in a condition was increased. However, the effect was not found to be significant for speed, DCM, or TTC. One of the causes was the relatively small size of the users group (N = 11). This led to low observed powers for all used tests, which did not reach a desired .80 for detecting a small effect, medium effect and large effect. A larger sample size would have led to more conclusive results.

The differences in risk compensation between the two groups appear minimal according to the data. It is possible that the effect would be different if another study would use a larger sample size. An alternative explanation for the result could be that the demographic used here consisting of mostly young adult university students might have influenced the effect of ecstasy use on risk compensation strategies. Perhaps young adult university students do not show a link to their risk compensation strategy of ecstasy use, whereas the general population would.
4.7 Hypothesis 7A and 7B: Amphetamine use

Hypothesis 7A: Users of ecstasy show more risk-taking behavior than non-users.
No significant effects of being a user or a non-user of amphetamine on risk-taking behavior were found. Thus, no evidence was found to support this hypothesis. One of the causes was the small size of the users group (N = 4). This led to the power of the used tests only reaching a desired .80 power to detect a large effect, and not a medium effect and small effect. Thus, a larger sample size would have led to more conclusive results.

Interestingly, non-users scored higher for risk-taking behavior than users, even though this difference was not significant. The data pointed in the opposite direction of the hypothesis and the findings discussed in the introduction. This was surprising, considering the research discussed regarding increased risk-taking behavior amongst users of illegal substances (Centers for Disease Control and Prevention, 1999; Chitwood et al., 2000; Friedman, 1998; Joe & Simpson, 1995; Kral, Bluthenthal, Booth, & Watters, 1998; Murray et al., 2003; Rhodes et al., 1990). This might, like in the case of the effects found for ecstasy use, have been due to the small sample sizes or due to the demographic used in this study.

Hypothesis 7B: Usage of ecstasy influences the risk compensation strategy.
Non-users showed a significant increase of risk-taking behavior across all three variables (reduced DCM, increased speed and reduced TTC) when the amount of shields given in a condition was increased. Users also showed an increase of risk-taking behavior across all three variables when the amount of shields given in a condition was increased. However, the effect was not found to be significant for speed, DCM, or TTC. One of the causes was the small size of the users group (N = 4). The power of the tests was too low (< .80) to reliably detect a small effect, medium effect and large effect. Thus, a larger sample size would have led to more conclusive results.

However, the differences in risk compensation between the two groups do appear to be minimal according to the data. The only exception was TTC, in which users appear to show stronger risk-compensation when given less shields. This effect was not significant and, as was mentioned, could very well be caused by the small sample sizes. The other option might be the demographic used for this study.

5. Conclusion
The risk homeostasis theory (Wilde, 1982) fits the findings regarding risk compensation in this study. This was not only found for the general sample, but also in a lot of cases for the
subgroups the participants were divided into (i.e., users versus non-users for all the different substances). Risk homeostasis thus seems to be present whether participants were substance users or not.

Since the only manipulation that was done to differentiate between the sessions was a change in the amount of protective measures, which was expected to only have an effect on the perceived risk level, it can be expected that the risk compensation was caused by changes in participants’ desired adjustment behavior and more specifically in participants’ perceived risk level. When looking at the model of the risk homeostasis theory (Wilde, 1982), one could argue that by playing the game for a while participants may have gone through a change in decision making skills or a change in skill at playing the game. However, the randomization of the order of sessions for participants should have negated any effect this would have on the results while not changing the effect of the different amount of protective measures per session. The outcome therefore supports the thoughts of Wilde (1982) on how changes in protective measures will simply lead to people taking more risks to compensate for the larger gap between their perceived risk level and target risk level. However, it is advised in future studies to also document the skills of participants to see if this played any role, especially if researchers do not randomize the order of sessions in their study.

Furthermore, several interesting findings were done regarding the moderating effect of substance use on risk compensation. Cigarettes users were found to generally adapt to changing risk levels similarly to non-users, but did generally show slightly riskier behavior in all situations. Marijuana users surprisingly turned out to almost be indistinguishable from non-users when it came to their risk compensation behavior. For the other substances (alcohol, cocaine, ecstasy and amphetamine) interesting differences were observed between the groups, but due to the size of either the group of users or non-users in these comparisons, only one of the groups actually showed sufficient significant effects for risk compensation. The other group would usually have too low power to reliably detect an effect, or at least a smaller effect ($f \leq .25$). Regardless some interesting comparisons could be made based on the direction the data pointed towards. Alcohol users seemed to show less risk compensation in riskier situations than non-users, and cocaine users seemed to generally show less risk-related behavior and showed more compensating behavior in risky situations compared to non-users. Similarly to marijuana users, ecstasy users seemed to show around the same amount of risk compensation as non-users. Finally amphetamine users generally also showed about the same risk-taking behavior as normal users. Some of the results regarding the illegal substances (cocaine, ecstasy and amphetamine) were rather unexpected, as it seemed these
substances did not show an increase in risk taking or decrease in risk compensation. Rather, the few cases where there were differences between users and non-users, users took less risks and showed more risk compensation. This may have had to do with the demographic that was used in this study mostly being young adult university students from the Netherlands, but was probably caused by the low amount of users included in this study for these substances. This led to very low power on all the tests to reliably detect any effect. Thus, even though the effects were not significant, it could be interesting to look at the hypotheses used in this study again with a larger sample size to see if any of the effects found here could actually be found to be significant either in this particular demographic or in a demographic that could be more easily generalized. For the effects that were found to be significant and any future effects of substance use that might still be discovered it is important to assess whether the difference lies in different target risk levels of the groups, or different perceived risk levels. As mentioned before, this study merely looked at a presence of risk compensation and used amount of protective measures as the independent variable. Although it was assumed this would influence the perceived risk level, differences between the users and non-users could be caused by different perceptions of these protective measures. However, differences might also be caused by the groups having different target risk levels to begin with, as was theorized before based on the link between substance use and sensation seeking (Kohn & Coulas, 1985; Schwarz, Burkhart & Green, 1978; Zuckerman & Neeb, 1980), and the link between sensation seeking and seeking out more risk and showing more risk-taking behavior (Zuckerman, 1979).

The general effects of different protective measures on risk-taking behavior and the moderating effects of substance usage on risk-taking behavior with different protective measures were all observed in a relatively short amount of time in this study. Wilde (1989) stated that risk compensation could take months, or even years. The findings in this study seem more in line with those of Glendon et al. (1996). Just like in the study by Glendon et al. (1996), this author theorizes that the reason for these more immediately observable changes in risk-taking behavior could very well be due to the immediate availability- and clarity of changes in protective measures between conditions. Furthermore, one could argue traffic situations would be a lot more complex than the spaceship game. It was presumably easy for participants to figure out that having 5 shields should make the spaceship game a lot safer than having 0 shields. Especially when compared to trying to figure out how much safer one is with the latest improvement in airbag technology or with a change in anti-lock brakes (ABS) in taxis (Grant & Smiley, 1993). This could take some more time and information.
that would take months or years to get, like Wilde (1989) argued. It is important to note that within the sessions themselves participants did not show any risk compensation when they lost shields. These results indicate that participants did actually need to be aware of a change in riskiness and needed some time to think about the riskiness of a situation to show risk compensation. Once a desired adjustment of behavior was chosen, participants needed new information regarding protective measures that were put in place to reevaluate the situation to adjust their behavior again. Apparently participants could not adapt to changes in protective measures remaining within the time of a session. This does still align with the concept of lagged feedback from the original model (Wilde, 1982), since people stuck to their risk-taking strategy once it was chosen until they had new information about the amount of protective measures they received the next session. The setup of this study simply may have led to quicker risk compensation behavior, since, as mentioned before, information about protective measures was more directly available and clear than in a real-life traffic setting. The outcomes therefore do not seem to conflict with the risk homeostasis theory (Wilde, 1982).

Most hypotheses regarding risk-taking behavior and substance use could not be supported with the current study. The results for these hypotheses regarding risk-taking behavior and substance use habits led to insignificant results. It is important to note that the power of the tests finding these insignificant results often were too low to reliably detect an effect, or at the very least a somewhat smaller effect ($f \leq .25$). One exception was the trend that was found in the data regarding the quantity of use of alcohol per time. This trend was found for relatively small groups and would have probably been significant if the sample would have been slightly bigger, since this would have also increased the power of this test. This supported findings made in earlier studies discussed in the introduction regarding the average quantity of alcohol consumption and risk-taking behavior (Cherpitel, 1993b; Cherpitel, 1995a as both read in Cherpitel, 1999; Fernie, Cole, Goudie & Field, 2010; Weafer, Milich & Fillmore, 2011).

The results found in this study help strengthen the position of the risk homeostasis theory, and will help to make the theory less controversial, since this study was designed keeping the criteria of Glendon et al. (1996) in mind and still produced results supporting the risk homeostasis theory. Additionally this study showed the risk homeostasis effect in a more controlled setting than the real-life traffic setting that most research on this theory has been conducted in. This shows the model of Wilde (1982) can very well be used outside of the context it was originally designed for. This author hopes it will inspire more research into the
other possible applications of the risk homeostasis theory in real-life settings outside of a traffic context.

In addition, this study also adds to the body of work regarding the influence of substance use on risk compensation strategies, and showed interesting trends on risk-taking behavior and substance use. It showed that it would be worth looking into differences in both risk-taking behavior and risk compensation strategies between users and non-users of the substances that were tested for using larger groups of participants in future studies to increase the power of the tests. Furthermore, studies looking at these effects regarding the substance marijuana should also be done in countries where marijuana is illegal; to see if there might be a difference in risk-taking behavior or risk compensation strategies between users and non-users or for participants with different user habits in such a study.

To conclude, as was discussed before in the introduction, risk-taking behavior leads to a lot of loss of life, time and resources. If better communication about protective measures would lead to a reduction of even one tenth of such losses, we could already expect to be saving 230,000 human lives every year and preventing 31.7 million accidents a year worldwide. This would lead to a lot less injuries, absence from work and loss of resources worldwide (“Safety and health at work”, 2016). With growing support for the risk homeostasis theory coming from this study and others, the next step will be to see if the risk homeostasis theory can be applied to other real-life settings besides those in a traffic context. If it can be applied in other settings, such as industry settings and in dangerous jobs such as firefighting or working in the police force, among others, it would be important to start looking at proper communication about protective measures. As Wilde (1982) already pointed out, changing protective measures will not result in much if people simply adjust their behavior based on their now lower perceived level of risk as compared to their target level of risk. Therefore, we must find ways to influence the perceived level of risk and the target level of risk of people in these settings. Proper communication about protective measures should help influence the perceived level of risk and target level of risk, since the information from this communication weighs in on the costs and benefits analysis people would be making when determining their target level of risk and should also help them to perceive the risk they are taking better. To make sure this is the case, we need to listen to the criticism of Hoyes and Glendon (1993), and find a way to measure target risk levels of participants. This way we can see what kind of communication helps change target risk levels of people to appropriate levels. Furthermore, the advice about communication of risk coming from Austin and Fischhoff (2012) might prove of paramount importance to help
improve communication about risk and protective measures. However, it is important to
remain critical of solutions to the communication issues regarding risk. Therefore, if the risk
homeostasis theory is supported in other real-life settings than traffic, it is important to start
researching and evaluating a proper way of communication about risks and protective
measures in those specific settings. This might be the way that is proposed by Austin and
Fischhoff (2012), but this author encourages more research into the possibilities and more
research to evaluate these possibilities. This way we can hope to find what the most effective
way of communication about risk and protective measures might be for each of these
settings. This might lead to an overarching optimal way of communicating about risk and
protective measures, but it might be too optimistic to conduct studies based on this
assumption. Therefore studying the best way of communication for each context separately
would be the safer approach to start with. And, if anything, we should have learned to
appreciate the importance of safety by now.

6. Limitations
Several promising results were found, but the current study does have several limitations that
need to be considered. One of these limitations has to do with the setting of the experiment.
Many different factors have been found to influence risk-taking behavior. An attempt was
made to control as many factors influencing risk-taking behavior as possible in the current
study, but not all factors could be controlled. Another limitation of the setting is the absence
of possibility of real harm. This may have led to participants behaving in a different way
than they would have done in a real-life traffic setting. On top of that, due to the researchers
observing participants playing, participants may have shown socially desirable behavior.
This effect could be especially prevalent for their answers about their use of (illegal)
substances, as participants may not want to admit to their use of such substances in a setting
where they are being observed by others.

The design of the experiment and the video game may have also distorted the data in
several different ways. As discussed earlier, for TTC and DCM the first shield was not
included in the analysis of shields left within each condition. This was due to severe
distortion of the data of these variables. The distortion made the data of the first shield
always look extremely low in risk-taking behavior as compared to the other amounts of
shields within conditions. Current results showed similar issues for the speed variable. It
seems that participants may have had to get used to the simulation again whenever a new
session (condition) begun. Another explanation could be that it had to do with the design of
the game. The game starts participants out on the lowest possible speed and with no meteors on the screen. Therefore, the data of the first shield could be expected to be distorted for all risk-taking behavior variables. The current results may simply be due to this problem with the current video game. Regardless of the cause, the first shield should have also been omitted from the comparisons within shield conditions for all variables, including speed. This would have resolved the issue with the distortion, whether caused by the design of the game, or the participants needing to get used to the simulation again.

Another issue with the design was the duration of the sessions in the experiment combined with the task being rather simple. Each session could take up to four minutes and a total of six sessions, including the test session, were played. It is possible that this led part of participants to increase their speed to try and lose their shields quicker, so the experiment would be done sooner. This could be caused by factors such as boredom or feelings of tiredness. This could have had an effect on the measurements between shield conditions and especially on the measurements between shields within the shield conditions. The randomization of sessions counteracted the effect for measurements between shield conditions. No such randomization of amount of shields left within sessions was possible and thus the results for these measurements could be distorted by this issue.

Several issues related to the moderating variables of different forms of substance use also need to be discussed. The assignment to different user groups in the case of recency of substance use, frequency of substance use and quantity of substance use were done based on information that could be seen as somewhat arbitrary. Although the decision was based on available information, this information was hard to call reliable as part of it came from online substance user communities. Furthermore, sample sizes were small for many comparisons that were made. In some cases only a few users or non-users of substances were present and the same could be said for the groups that were made based on recency of substance use, frequency of substance use and quantity of substance use. Furthermore, the sample size of the entire study consisted of only 69 participants. This made the power of a lot of the used tests rather low, especially for detecting smaller effects ($f \leq .25$). This led to a lot of issues finding significant effects for many of the hypotheses that may have otherwise been found, and the small sample size also makes the results found hard to generalize as well. In addition, using a questionnaire to assess substance use is not the most reliable way, since participants may not have been completely truthful. It would have been preferable to have a more reliable measure of substance usage.

The same issue of sample size needs to be noted for the entire sample, since the
entire study used a sample of only 69 participants. This makes any results found in this study hard to generalize and also lowers the reliability of the study. The power found for the tests done on larger groups within this study was somewhat higher and did find several effects. However, these tests were often still unable to reliably (minimum power of .80) detect smaller effects ($f \leq .25$) and thus may have still missed some effects. Another issue with the current sample was that it consisted mainly of young female students. This may have influenced the results as well, as it is well-known that men are often more risk-taking than women and generally report more use of substances than women in earlier research in the Netherlands (“Attitudes of Europeans towards tobacco and electronic cigarettes”, 2015; Van Laar et al., 2016; Van der Pol & Van Laar, 2015).

A final issue regarding this study was already brought up in the introduction by several critics of the risk homeostasis theory. Since no guidelines are given by the risk homeostasis theory to assess the target level of risk (Wilde, 1982), this study was unable to measure target levels of risk for participants. The study did include several forms of substance use, which have previously been found to influence the amount of risk people are willing to take. However, this is but one of many factors related to the target risk level of individuals, and no other such factors were included in the present study.

7. Future studies

More research into the phenomenon of risk homeostasis is necessary, both within the field of car traffic and outside of it. As more testing in controlled environments is needed, it is important that future studies try to control for as many factors as possible. Furthermore, more realistic simulations of risky situations could help to make results found in controlled studies more easily generalized to real-life settings. More real feeling risks for participants might also help combat the issue of possible boredom that often comes up with simpler tasks.

Another issue that needs to be overcome is the difficulty of falsifying the risk homeostasis theory. Future studies should therefore attempt to establish a baseline for the desired risk level of individual participants. This would mean that risk homeostasis could be analyzed on an individual level, which is the level the theory was supposed to be measured on according to criticism discussed in the introduction.

Future researchers also need to keep in mind that if the task participants need to perform in the controlled setting is different from real-life settings, they might need to get used to the setting at first. It is therefore important that future studies keep careful track of
their data and stay alert of trends of different risk-taking behavior during the start of their experiment. By improving studies in the aforementioned way more reliable results will be found in future studies into risk homeostasis and the theory will be more easily falsified.

Besides research done in controlled environments, it is important to also start to try and test the risk homeostasis theory in other real-life settings, such as within the aviation industry, the chemical industry, the police force, the firefighting force and many other settings. If the theory is applicable in these settings, this should lead to research about proper communication about risks and protective measures in these settings. This research would be invaluable, since the insights regarding such communication could lead to the saving of many lives, and a lot of time and resources worldwide.

Future studies comparing substance users, and substance use habits (e.g., recency of use, frequency of use and quantity of use (per time) on their risk-taking behavior and risk compensation strategies could also prove fruitful. In these studies it would be important to use larger sample sizes. This way the power of their tests should be adequate to reliably detect smaller effects for some groups and hypotheses that this study struggled to reliably detect. Furthermore, it would be important to recruit their sample based on interest in the differences for certain substances. The studies looking into risk compensation and risk homeostasis should also follow the guidelines given regarding the research of risk homeostasis. Using larger sample sizes to improve the power of tests and improving study designs based on the aforementioned advice would shed more light on the influence of substance use and substance use habits on risk-taking behavior and risk compensation strategies. In addition, future studies should try and use a more reliable way to assess substance usage, since questionnaires on the subject of substance use cannot be expected to be answered entirely truthfully by participants.
References


Appendices

Appendix A. The questionnaire

Introduction

The following questionnaire will take about **20 minutes to complete**.

The questionnaire is about **five different topics**. The questions are grouped based on these topics, so do not be surprised if the topic changes when you go to a new page.

We would like to restate that this research is **confidential**, and you will be completely **anonymous**. The results will be used to conduct statistical analysis for our master thesis project about the risk homeostasis theory.

**The risk homeostasis team**

Jop Groeneweg  
Doris van Duijl  
Gerwin Hulzing  
Maurits van der Sluis  
Gwyneth Wolfert
What is your participant number? If you are unsure, check your post-it, or ask one of the supervisors.

What is your gender?
- Male
- Female

What is your age in years?

What is your highest completed level of education?
- VMBO
- HAVO
- VWO
- MBO
- HBO
- WO Bachelor
- WO Master

When was the last time you consumed alcohol?
- Never
- More than 3 months ago
- 1-3 months ago
- 2 weeks-1 month ago
- 8 days-2 weeks ago
- 4-7 days ago
- 2-3 days ago
- 0-1 days ago
How often do you averagely consume alcohol?
- Less than once every 6 months
- Once every 3-6 months
- Once every 1-3 months
- Once every 2 weeks-1 month
- Once every 1-2 weeks
- Once every 4-6 days
- Once every 2-3 days
- Once every day

How much alcohol do you averagely consume on the occasion that you consume alcohol? 250 Ml of 5% beer equals 1 Dutch standard drink.
- < 1 standard drink
- 1-2 standard drinks
- 2-3 standard drinks
- 3-4 standard drinks
- 4-5 standard drinks
- 5-6 standard drinks
- 6-8 standard drinks
- > 8 standard drinks

When was the last time you smoked cigarettes?
- Never
- More than 3 months ago
- 1-3 months ago
- 2 weeks-1 month ago
- 8 days-2 weeks ago
- 4-7 days ago
- 2-3 days ago
- 0-1 days ago
How often do you averagely smoke cigarettes?
- Less than once a month
- Once every 2 weeks-1 month
- Once every 1-2 weeks
- Once every 4-7 days
- Once every 1-3 days
- 1-4 times every day
- 5-10 times every day
- More than 10 times every day

How much cigarettes do you averagely smoke on the occasion that you smoke?
- Less than 1 cigarette
- 1-2 cigarettes
- 2-3 cigarettes
- 3-4 cigarettes
- 4-5 cigarettes
- 5-6 cigarettes
- 6-7 cigarettes
- More than 7 cigarettes

When was the last time you used marijuana?
- Never
- More than 6 months ago
- 4-6 months ago
- 2-4 months ago
- 1-2 months ago
- 1 week-1 month ago
- 3-7 days ago
- 0-2 days ago
How often do you averagely use marijuana?
- Less than once every 6 months
- Once every 3-6 months
- Once every 1-3 months
- Once every 2 weeks-1 month
- Once every 1-2 weeks
- Once every 5-7 days
- Once every 2-4 days
- Once every day or more

How much marijuana do you averagely use on the occasion that you use marijuana? *Prerolled joints in the Netherlands contain approx. 0.3 grams of marijuana*
- Less than 0.2 grams
- 0.2-0.4 grams
- 0.4-0.6 grams
- 0.6-0.8 grams
- 0.8-1.0 grams
- 1.0-1.2 grams
- 1.2-1.4 grams
- More than 1.4 grams

When was the last time you used cocaine?
- Never
- More than 1 year ago
- 6-12 months ago
- 3-6 months ago
- 1-3 months ago
- 2 weeks-1 month ago
- 8 days-2 weeks ago
- 0-7 days ago
How often do you averagely use cocaine?
- Less than once every year
- Once every 6-12 months
- Once every 3-6 months
- Once every 1-3 months
- Once every 2 weeks-1 month
- Once every 8-14 days
- Once every 2-7 days
- Once every day or more

How much cocaine do you averagely use on the occasion that you use cocaine?
- Less than 50 milligrams
- 50-100 milligrams
- 100-150 milligrams
- 150-200 milligrams
- 200-230 milligrams
- 250-300 milligrams
- 300-350 milligrams
- More than 350 milligrams

When was the last time you used ecstasy?
- Never
- More than 1 year ago
- 6-12 months ago
- 3-6 months ago
- 1-3 months ago
- 2 weeks-1 month ago
- 8 days-2 weeks ago
- 0-7 days ago
How often do you averagely use ecstasy?

- Less than once every year
- Once every 6-12 months
- Once every 3-6 months
- Once every 1-3 months
- Once every 2 weeks-1 month
- Once every 8-14 days
- Once every 2-7 days
- Once every day or more

How much ecstasy do you averagely use on the occasion that you use ecstasy?

- Less than 50 milligrams
- 50-75 milligrams
- 75-100 milligrams
- 100-125 milligrams
- 125-150 milligrams
- 150-175 milligrams
- 175-200 milligrams
- More than 200 milligrams

When was the last time you used amphetamine?

- Never
- More than 1 year ago
- 6-12 months ago
- 3-6 months ago
- 1-3 months ago
- 2 weeks-1 month ago
- 8 days-2 weeks ago
- 0-7 days ago
How often do you averagely use amphetamine?

- Less than once every year
- Once every 6-12 months
- Once every 3-6 months
- Once every 1-3 months
- Once every 2 weeks-1 month
- Once every 8-14 days
- Once every 2-7 days
- Once every day or more

How much amphetamine do you averagely use on the occasion that you use amphetamine?

- Less than 20 milligrams
- 20-40 milligrams
- 40-60 milligrams
- 60-80 milligrams
- 80-100 milligrams
- 100-120 milligrams
- 120-140 grams
- More than 140 milligrams

Thank you for completing our questionnaire.

You can now collect your money or credits for participating.

Next week we will e-mail you a list of all the achieved scores. This list will be coded by means of participants numbers, so please do not forget your participant number! The three participants with the highest scores will receive a prize (€50, €30 and €10). You will receive further information via e-mail.
Appendix B. Formulas for the risk-taking behavior variables

The formula used to compute the variable ‘speed’ was:

\[ speed_p = (2.7 + (difficulty \times 0.5)) \times 100 \]

Difficulty is always a value between 1 and 13 (based on the difficulty levels). This formula yields speed values with a minimum of 320 pixels per second and a maximum of 920 pixels per second.

The formula used to compute ‘distance to the closest meteor’ (DCM) was:

\[ distance = \sqrt{(closest \, meteor \, location \, x)^2 + (closest \, meteor \, location \, y - ship \, location \, y)^2} \]

The Pythagorean Theorem was used to create this formula. This formula yields the distance, in pixels, between the spaceship and the meteor closest to it.

The formula used to compute ‘time to collision’ (TTC) was:

\[ TTC = \frac{meteor \, in \, path \, location \, x - 109}{speed_p} \]

The TTC variable is calculated using the ‘meteor in path location x’ variable. This is the x-coordinate of the meteor on the path of the spaceship. This variable can be found in the steplog file. Afterwards the value 109 has to be subtracted from this variable as the spaceship is not displayed at the leftmost side of the screen but 109 pixels to the right from it. This formula yields the time, in seconds, until a collision between the spaceship and the meteor in its path will occur.
Appendix C. The information letter

Information letter - Risk homeostasis in gaming

Welcome and thank you for coming! You are going to play a computer game and fill in a questionnaire. Before you start, please read this information letter and sign the informed consent. Your participation is completely anonymous and voluntarily. Your records are coded by means of a participant number (see the post-it). You will need to enter this number when starting the game and the questionnaire. Please double check when entering your number, this is important. If you would like to stop the experiment you may do so at any moment. The results of this study will be used in SPSS to conduct statistical analyses for our master thesis about the risk homeostasis theory.

The game
The game is about a little spaceship in a galaxy not so far away on its way to deliver very valuable cargo. The spaceship is in a hurry and has to reach its destination as soon as possible. Unfortunately, the ship runs into a thick cloud of meteors. You are the ship’s captain and you have to stay on your toes to dodge the danger and get through. The goal is to go as fast as you can (a faster speed will result in more points) but also try to avoid the meteors (a collision with a meteor will cost you a life). You will receive specific instructions about the game (e.g. which buttons to use etcetera) when starting the game.

Instructions
Please pay attention only to your own computer screen. Also, please do not make noise. When you have a question raise your hand and one of us will come to you.

After you have read and completed the informed consent, please login with your UL account (Some of the computers are already logged in, if so, do not log in with your own UL account). When your desktop is completely loaded raise your hand. We will start the game for you. After you have finished the game please raise your hand and we will start the questionnaire for you. Please do not forget to enter your (correct) post-it number both in the game and questionnaire! When you completed the questionnaire you can collect your money or credits for participating.

Any questions?

Remarks or complaints afterwards can be directed towards the senior researcher:

Jop Groeneweg
Groeneweg@fsw.leidenuniv.nl
Appendix D. The informed consent form

**Informed Consent** - Risk homeostasis in gaming

In this experiment we will test the risk homeostasis theory by means of a computer game. The experiment will take about 45 minutes. You will be compensated for your time by receiving 2 credits or €6.50. By signing the form you agree with the following statements.

- I have read the information letter. I could ask additional questions. Questions that I had have been answered adequately. I have had sufficient time to decide whether or not I participate.

- I am aware that participation is completely voluntary. I know that I can decide at any moment not to participate or to stop. I do not need to provide a reason for that.

- My responses are processed anonymously or in a coded way.

- I give consent to use my data for the purposes that are mentioned in the information letter.

I consent to participating in this study.

Name of participant: ___________________________________________________

Signature: ____________________________________________________________

Date: _____/_____/______
Appendix E. Game instructions

Instruction at the start

Dear participant,

You are now going to play a video game in which you control a spaceship that is flying through a field of meteors. You need to make sure the ship has a safe flight. If your ship collides with a meteor, it gets destroyed and the round is over. At the start of each round (5 in total) you will receive a certain number of shields. You see these shields at the left upper corner. These shields serve as ‘lives’. Each time you collide with a meteor, a shield will disappear. When you run out of shields, the round is over.

The up and down arrow keys control the movement of the ship. You also have the option to control the speed of the ship: pressing the right arrow key makes the ship fly faster, while pressing the left arrow key slows the ship down.

During the game you will gain points per second. The amount of points you gain depends on (1) your total flying time (so don’t run out of shields!) and (2) your speed: the faster you fly, the more points per second you gain. You will start with a practice round.

Good luck!

Instruction at the end

Thank you for playing the game! You can now raise your hand and ask for the questionnaire.
Appendix F. The debriefing

**Debriefing – Risk Homeostasis in Gaming**

The aim of this study was to test the risk homeostasis theory and the moderating role of substance use, music preference, participation in sports and masculinity. Risk homeostasis means that you show more risk behavior when you feel safer, for example cycling faster and more dangerously when wearing a helmet. In the computer game we measured risk behavior by measuring your speed and proximity to meteorites in interaction with the amount of shields present.

We expect to find that:
1. People take more risk when they perceive the situation to be safer (so when you have more shields left, you will show more risky behavior);
2. Masculine men or women show more risk behavior;
3. Participation in sports (depending on the kind of sport and the position within this sport) influences risk behavior;
4. More recent and frequent use of substance, and higher quantity per substance use will be related to higher risk-taking.
5. Music preference and its resulting emotional arousal influence risk behavior.

Your contribution is important to understanding how these factors influence risk-taking behavior, as safety implementations and interventions can be applied more effectively.

Questions, remarks or complaints afterwards can be directed towards the senior researcher:

Jop Groeneweg
Groeneweg@fsw.leidenuniv.nl