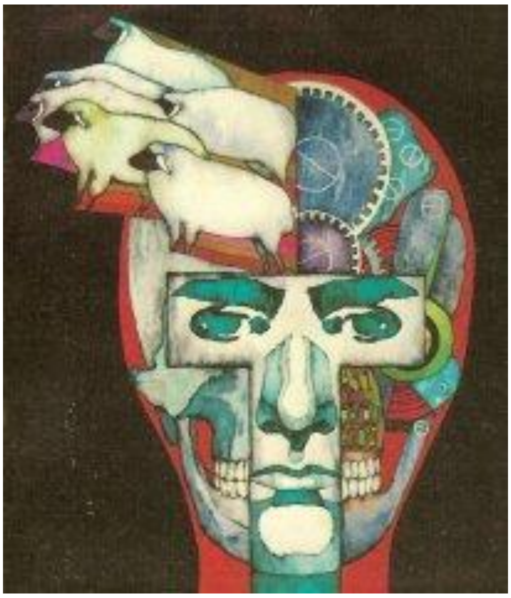
Do geeks dream of electric sheep?
Exploring the attitude of geeks toward robots



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Abstract

Due to the improvement of the functions of humanoid robots, the concept of anthropomorphism is a relevant research topic in the field of human-robot interaction. In order to supplement the concept of 'geekism' – which is defined as the initial likelihood of an individual to intellectually delve into the underlying mechanisms of technological systems, based on a strong intrinsic motivation (Schmettow and Drees, 2014) – we tested the tendency of so-called 'geeks' to anthropomorphize robotic agents.

Implementations about a low tendency were based on the three-factor theory of anthropomorphism, developed by Epley, Waytz, & Cacioppo (2007) and tested by the means of the perceived humanness scale and an adaption of the Stroop priming task. Mixed-effects regression analysis revealed no statistically significant results.

In the scope of this study it could not be indicated that 'so-called' geeks have a tendency toward anthropomorphism that significantly differs from other people. Moreover, explanatory attempts of Epley et al. (2007) about the occurrence of anthropomorphism due to a complex inductive process could not be confirmed. Yet, correlational analysis between personality concepts revealed a moderate positive correlation between computer enthusiasm and need for cognition, supporting the assumption that those two features form the core of 'geekism'. Finally, although it could be shown that individuals with computer enthusiasm have no preference for order, the need for closure does not seem to be related to the concept of geekism.

Due to possible research limitations future studies on the relation between geekism and anthropomorphism should focus on the addition of sociality to the research model, which is one of the three factors within the theory of Epley et al. (2007), the use of a method that is able to detect whether anthropomorphic processing takes place on an automatic level, and an explicit measure of anthropomorphism that includes an affective component.

Samenvatting

Omwille van de verbetering en groeiend gebruik van humanoïde robots en hun functies, is het antropomorfisieren hiervan een relevant onderwerp in het onderzoek over de mens-robot interactie. Om het concept geekisme aan te vullen – wat gedefineerd kan worden als de individuele aannemelijkheid zich op basis van intrinsieke motivatie met technische systemen bezig te houden om diens onderliggende werking te begrijpen (Schmettow and Drees, 2014) – werd getoetst in hoeverre zogenaamde 'geeks' geneigd zijn om robots the antropomorfiseren.

De verwachtingen van een lage neiging zijn gebaseerd op de 'drie-factoren theorie van antropomorfisme', ontwikkeld door Epley, Waytz, & Cacioppo (2007) en werden door middel van de pereived humanness scale en een adaptie van de Stroop priming taak getoetst. Een mixed-effects regressie analyse van de data heeft geen statistisch significante resultaten opgeleverd.

In het kader van deze studie kon niet worden aangetoond dat zogenaamde 'geeks' zich significant van andere personen onderscheiden wat het antropomorfiseren van robots betreft. Bovendien kon de poging om antropomorfisme door een complex inductief proces te verklaren niet worden bevestigd. Echter, correctioneel onderzoek tussen geïnvolveerde persoonlijkheids-concepten toonde aan dat computer enthousiasme en need for cognition positief aan elkaar zijn gerelateerd, waardoor ondersteund wordt dat 'geekism' uit deze twee componenten bestaat. Hoewel individuen met computer enthousiasme geen neiging tot een preferentie voor orde schijnen te hebben, kon geen verband tussen 'geekism' en need for closure worden aangetoond.

Omwille van mogelijke limitaties wordt aanbevolen om in toekomstig onderzoek over geekisme en antropomorfisme erop te focussen om de derde factor 'sociality' aan het onderzoeksmodel toe te voegen, een methode te gebruiken die in staat is vast te stellen of antropomorfische informatieverwerking op een automatisch niveau plaatsvindt en een expliciete meting van antropomorfisme af te nemen die een affectieve component omvat.

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1. Introduction

We occasionally describe our dog as being sad or disappointed as soon as we leave the house or accuse our computers as being stubborn when they do not work the way we want. We personify economic events and claim that we need to fight against them as if they were an enemy of flesh and blood and imagine our god as being wrathful when a hurricane or a flood destroys our houses. This phenomenon of attributing humanlike features to nonhuman agents is called anthropomorphism (Epley, Waytz, & Cacioppo, 2007).

Anthropomorphism has recently become more and more the focus of attention, especially when it comes to Human-Computer Interaction, a field that includes computer science, engineering, as well as artificial intelligence and its influence on the beliefs and actions of users (Waytz, Cacioppo, & Epley, 2010). The development of artificial intelligence in form of robotic agents has been immensely improving, presenting some complex human cognitive or physical capacities (Waytz et al., 2010). Some robotic devices are able to perceive and express emotions, to respond to spoken language, to develop social competencies through interaction with humans, to execute tasks without command, to identify and track people and to travel autonomously to destinations while avoiding hindrances (e.g. Fong, Nourbakhsh, Dautenhahn, 2003; Nourbakhsh, Bobenage, Grange, Lutz, Meyer, & Soto, 1999). Because of these accomplishments, robots are able to replace human beings, as well as to assist them in meeting certain goals. Professional service and domestic robots, for instance, are designed to help people in their work place or with tasks in the household (Fong et al., 2003). But the ability to socially interact with human beings has even broadened the scope in which robots are used, ranging from services as a museum tour-guide (Nourbakish et al., 1999) to an interactive partner for the elderly (Montemerlo, 2002) and even to a so-called ‘persuasive machine’, a robot that is used in therapeutic contexts in order to alter an individual’s behavior or attitude (Werry, Dautenhahn, Ogden, & Harwin, 2001). But to ensure an effective interaction between humans and robots, the introduction of social robots asks for acceptance from the user, since the social engagement with and the reliance on a non-living agent might feel very strange or even uncomfortable. Anthropomorphism is expected to facilitate this acceptance (e.g. Nass, Moon, Fogg, Reeves, & Dryer, 1995; Duffy, 2003; Fong et al., 2003). Recently it has been suggested that people might differ individually in the extent to which they anthropomorphize.

The three-factor theory of anthropomorphism by Epley, Waytz, and Cacioppo (2007) suggests that we can talk of an individual tendency or likelihood to anthropomorphize non-human agents which is determined by three personal features. An investigation of these features may allow predictions about one’s behavior towards non-human agents and since the anthropomorphism of non-human robotic agents might lead to some dangers (e.g. the allocation of responsibility (Culley and Madhavan, 2013)) as well as to benefits (e.g. more social and cooperative behavior when watched by human-like artificial eyes (Haley & Fessler, 2005)) we consider it important to investigate the extent of anthropomorphism of people that are most likely to be working with robotic agents: so-called ‘geeks’.

The term ‘geekism’ has been defined as a continuous trait which represents the extent to which one is intrinsically motivated to intellectually delve into the functioning of technological systems (Schmettow & Drees, 2014). Yet, there is not much known about the concept of ‘geekism’, which is why an investigation of the initial tendency of anthropomorphism could add some important information to its understanding, especially with regard to the way so-called geeks perceive the technical devices they are engaged with.

Thus in favor to approach an answer to the question to what extent so-called ‘geeks’ tend to anthropomorphize, we will first discuss some findings about what is understood of being a ‘geek’ in psychological terms. Secondly, we will have a look on the concept of anthropomorphism and attempts of its definition. Finally we will try to formulate implications about the extent to which this group of individuals may anthropomorphize robotic agents, based on the three-factor theory of anthropomorphism by Epley et al. (2007).

1.1 Geeks and geekism

Once used as an insult to humiliate and play down intelligent outcasts that were strongly interested in certain and maybe unusual subjects, the term ‘geek’ has become more positive and richer in its meaning nowadays than in the past. Long stereotyped as having low social skills and being chronically lonely, the community of the so-called ‘geeks’ can be perceived as a thorough subculture (McArthur, 2008), providing the possibility to interact with likeminded peers (O’Brien, 2007; Schmettow & Passlick, 2013). O’ Brien (2007) further states that most individuals in her multi sample interview study, who display Computer Technology Talent (CTT), demonstrate high verbal skills and due to the commercial character and rising popularity of digital communication nowadays, have more possibilities to combine their passion for technology with the engagement in social interactions. But more importantly than the compatibility between mainstream and personal interest, is that according to McArthur (2008), the label ‘geek’ has transformed from being a freak to being an *expert*. But what does the term ‘geek’ actually involve, if not the stereotype of the social inhibited youngster, and how does it relate to being an expert?

The ‘geek’-subculture has its roots in the United States of the 1940s, when computer programming and hacking emerged (Raymond, 2002). ‘Real programmers’ or ‘hackers’, as they were called, typically had their background in engineering or physics (Raymond, 2002). Although often linked to computers, it has been pointed out that so-called ‘geeks’ may be interested in various fields ranging from comic books, over games to trivia, most of them being somewhat related to technology (McArthur, 2008; Schmettow and Passlick 2013). Despite of the numerous fields of interest, a central aspect of ‘being a geek’ seems to be that a person becomes an expert in one or more of these topics. In the scope of their interview study Schmettow and

Passlick (2013) indeed identified ‘being an expert in a subject area’ as one of the key characteristics for the interviewed self-proclaimed ‘geeks’. Some of the interviewees described that they liked to use their technological expertise for the manipulation or improvement of devices. Diana (2008) also stated that this active engagement with technology may be one of the most characteristic features of so-called geeks.

At this point the question arises what psychological factors can account for a so-called ‘geek’ to become an expert in technology. Several studies support the idea that extrinsic as well as intrinsic motivational factors might be involved. Bitzer, Schrettl and Schröder (2006) for instance argue that private financial benefit and increasing chances on the job market are two extrinsic factors. In addition, in the scope of their interview study Schmettow and Passlick (2013) identified positive acknowledgement from like-minded experts as a factor that possibly facilitates extrinsic motivation to gain expert knowledge.

Although economic success and appreciation by peers are important benefits, the fact that ‘geeks’ are suggested to become experts due to an intrinsic motivation seems even more characteristic. According to the interview study of Schmettow and Passlick (2013), some of the self-proclaimed ‘geeks’ named aspects such as situations of accomplishment that are related to their field of expertise, being part of a community, exchanging knowledge, objectivity and the use of scientific standards (for instance while searching for topic-relevant information) motivational. Central to all this seems that so-called ‘geeks’ have a strong intrinsic interest in technology and, with a great deal of perseverance, desire to intellectually dive into the functioning of (technological) systems. Schmettow, Noordzij and Mundt (2013) coined this motivation as ‘technology enthusiasm’. Moreover, Schmettow and Mundt (2012) found that students who participate in a technical study have, next to computer enthusiasm, a strong need for cognition.

Cohen, Stotland and Wolfe (1955) defined the need for cognition as “a need to structure relevant situations in meaningful, integrate ways. It is a need to understand and make reasonable the experiential world” (p. 291). Later Cacioppo, Petty and Kao (1984) additionally described need for cognition as “an individual’s tendency to engage in and enjoy effortful cognitive endeavors” (p. 306). The technical students in the study of Schmettow and Mundt (2012) therefore seem to enjoy exploring and learning to a greater extent than other students. Moreover people high in need for cognition showed stronger associations with ‘geekism’-related expressions (e.g. ‘understand’, ‘configure’) in an adaption of the Stroop priming task (Schmettow, Noordzij, and Mundt, 2013). Due to these findings, the two features computer enthusiasm and need for cognition are suggested to form the core of ‘geekism’ (Schmettow and Mundt, 2012; Schmettow and Passlick, 2013). Therefore Schmettow and Drees (2014) concluded, that geekism can be described as the likelihood to intellectually delve into the functioning of technical systems in order to understand them.

Within the scope of their interview study, Schmettow and Passlick (2013) moreover suggested that, next to need for cognition, geeks may experience curiosity and a desire or feeling of being in control while dealing with technological devices.

Need for control is described as "the extent to which people generally are motivated to see themselves in control of the events in their lives" (Burger, 1992, p. 6, as cited in Epley et al., 2007). Some participants for instance claimed that control over situations and products have motivated them to engage in "challenging and eventually successful behavior" (p.20). Thus although no clear evidence could be found with regard to need for control, this could be another important factor that motivates 'geeks' to obtain expertise knowledge.

Summed up so-called geeks are thought to have gained their expertise especially due to the fact that they are intrinsically motivated to intellectually dive into the underlying technical systems in order to fully understand them. This much about the motivational factors that make 'geeks' obtain their expertise about technical devices. Yet, there is not much known about the way geeks *perceive* those technical devices, for instance when they resemble a human being, such as humanoid robots.

1.2 Anthropomorphism

Anthropomorphism is not an effect recently discovered in the study of human-robot interaction, but is known since antiquity. Consisting of the Greek notions anthrōpos (human) & morphē (shape, form), the effect is known to be first described by Xenophanes (ca. 560-478 B.C.) when he noticed that gods or supernatural agents commonly strongly resemble their believers (Hergenhahn, 2009). He based his notion on the observation that the gods of the Greeks feature the fair skin and bright eyes of the people who believe in them, whereas folks with dark-colored skin describe their gods as dark-eyed and dark-skinned. But the projection of humanlike features on agents actually goes beyond the outer appearance. Indeed research has shown, that gods (e.i. Barrett and Keil, 1996) and other nonhuman agents (Hergenhahn, 2009) might be expected to have character traits, attitudes and feelings. Epley et al. (2007) therefore widen the definition of anthropomorphism by claiming that it is more than a mere description of a nonhuman agent's behavior or its bodily features, but "a process of inference about unobservable characteristics of nonhuman agents" and therefore the attribution of humanlike character traits, mental and emotional states (p. 865).

Yet, a non-human agent may have bodily features or perform certain actions that result in a heavier anthropomorphic response than others. Bodily properties like two arms, two legs and detailed facial attributes are found to be such features (DiSalvo, Gemperle, Folizzi, & Kiesler, 2002). It seems that the ability to move autonomously also increases the extent to which one anthropomorphizes a robot. This suggestion is based on the 'uncanny valley' described by Masahiro Mori in 1970, which models the effect of autonomous movements and humanlike appearance on the emotional response of the perceiver (Mori, 1970). When it comes to the ability to move autonomously, Mori (1970) suggests that the emotional response of the observer towards the agent is even more exaggerated as if it was not moving, since movement is generally interpreted as a sign of life. This is in line with research from Salem, Eyssel, Rohlfing, Kopp and Joublin (2013), which indicates that the conductance of gestures enhanced the degree to which participants perceived a robot as humanlike and even as likable.

Although it was already inferred that bodily features and autonomous movements that resemble those of human beings increase the anthropomorphic response, anthropomorphism was expected to be a process that happens to be invariant rather than individually different: It has been described as a common and chronic tendency of judging nonhuman agents that is taking place automatically (i.e.: Guthrie, 1993 and Mitchell, Thompson and Miles, 1997; cited in Epley et al. 2007). However Epley et al. (2007) have suggested that human beings also individually vary in the extent to which they anthropomorphize and therefore developed a three-factor theory of anthropomorphism. Consistent with Xenophanes' initial observation, Epley et al., (2007) assume that anthropomorphism is a form of generalization from human beings to nonhuman agents. According to their assumptions, this inductive process is determined by three psychological factors: elicited agent knowledge, effectance motivation and sociality motivation (SEEK). It is this theory that we will make use of in order to make inferences about the extent to which so-called 'geeks' anthropomorphize non-human agents.

1.3 Inferences about the individual tendency of geeks to anthropomorphize

i. Elicited agent knowledge

Elicited agent knowledge is the cognitive element of the three-factor theory of anthropomorphism and functions as the primary base for the inductive process about unknown non-human agents (Epley et al., 2007). The importance of 'elicited agent knowledge' for the individual extent to which one tends to anthropomorphize can be best introduced by the means of a short thought experiment.

When your new neighbor has neatly trimmed your hedge that marks the border between his and your garden without announcing it, you are wondering which reason he might have had to do so. Was he annoyed by single sticks of your hedge looming into his garden or did he just want to be nice and do you the favor of helping you with gardening? While thinking about which possibility is most likely, research suggests that you will rely on what you yourself would have thought in his position (Keysar & Barr, 2002; Epley, Keysar et al., 2004): because you lack information about the personality of your new neighbor, you are using yourself and your own mental states as a reference in order to make sense of his deeds. These egocentric representations about behaviors and their underlying intentions are described as very detailed, complete and readily accessible. Therefore the activation of the egocentric bias when making inferences about other agents is thought to be virtually automatic. According to Ames (2004) the probability that one will refer to egocentric knowledge is even higher, the more similarity one perceives between the other person and oneself. Here the question arises whether this also applies to the attempt of making sense of a humanoid robot that is conducting a very humanlike task, such as washing a window. In the scope of their three-factor theory, Epley et al. (2007) suggest that exactly this is the case. They assume that the inductive process based on egocentric representations does not only hold for other people, but is also taking place when somebody is anthropomorphizing a *nonhuman* agent. In agreement with this assumption, Iacoboni, Lieberman, Knowlton, Molnar-Szakacs, Moritz, Throop, & Fiske (2004) have shown that when a person is making anthropomorphic judgments about a nonhuman agent, the same neural systems are activated as when making inferences about other human beings. Yet, as we have seen, human beings are expected to vary individually in their tendency to anthropomorphize nonhuman agents and thus in their tendency to rely on egocentric knowledge when judging them.

According to Epley et al. (2007) this variation is determined by the likelihood to which the three inductive phases *activation, amendment* and *application* might occur. To give an example, the inductive process could for instance start off with the initial situation of perceiving the humanoid robot that executes the very humanlike task of washing a window. As we have seen, the strong resemblance to a human being and the high accessibility of egocentric representations are anticipated to result in a rapid *activation* of these very same representations. In other words we are trying to make sense of the robot and the way it neatly cleans the window without missing any stain by referring to ourselves, when performing the same task. In the second phase of the inductive process the anthropomorphic representations one has made on the basis of egocentric knowledge might be *amended* due to the co-activation of alternative knowledge. In the case of our window-washing robot, the idea that we are dealing with an autonomous being that consciously perceives the stains might for instance be accompanied by information about sensory detection systems in cameras. Finally, in the third phase, the activated representations of conscious perception and technical detection systems might be integrated and thus lead to a corrected explanation which is *applied* to the agent. In other words the alternative explanation of sensory detection systems in cameras, has led to the correction of the initial anthropomorphic response towards the robot: due to active reasoning about the two possible explanations, we do not think that its ability of detecting all stains on the window is based on conscious perception after all. Thus, as the second and third phase of the process indicates, the anthropomorphic inferences about the nonhuman agent might be corrected under the influence of alternative knowledge and an effortful reasoning process. Indeed it has been shown that the correction of initial inferences about unknown agents leads to the reduction of egocentric biases (Epley, Keysar, et al., 2004). This requires however that alternative knowledge is available.

Epley et al. (2007) connect the availability of alternative models of agency to the extent to which one has been exposed to these or similar agents. Children that live in industrialized cultures for instance would, as they suggest, tend to anthropomorphize animals more than technical devices and robots, due to a lack of experience with them in daily life contexts. As we have seen earlier in this essay, the key feature of 'geekism' is expected to be the strong likelihood of frequent engagement (or experience) with and expert knowledge in the field of technology (e.g.: Schmettow and Passlick, 2013). This leads us to the assumption that individuals with a tendency toward ‘geekism’ probably have better access to alternative information about the functioning of technical agents such as robots and therefore have the possibility to correct the anthropomorphic inferences through a process of reasoning. As we have seen in the description of the second and third inductive phases, alternative knowledge however, needs to be co-activated and integrated by an effortful reasoning process in order to alter anthropomorphic assumptions. A determinant that heightens the likelihood of this co-activation and integration is according to Epley et al. (2007) the need for cognition.

In their three-factor theory of anthropomorphism Epley et al. (2007) claim ‘need for cognition’ to be the dispositional determinant of elicited agent knowledge. Based on research of Cacioppo, Petty, Feinstein, & Jarvis (1996) it has been shown that people who are high in the need for cognition and therefore enjoy effortful thinking, are more likely to correct readily available prejudices. Epley et al. (2007) assume that individuals scoring high in the need for cognition, would show “less reliance on readily accessible anthropomorphic information and instead […] an increased activation of alternate representations” (p.). As we have seen earlier ‘geekism’ is expected to partly consist of the ‘need for cognition’ (Schmettow and Mundt, 2012). On the basis of these findings and inferences we suggest that people who show a high tendency towards geekism are more likely to correct anthropomorphic representations about an agent through engaging in an effortful reasoning process.

In sum the availability of expert knowledge in the field of technology and the profound likelihood of engaging in effortful thinking, is expected to make so-called ‘geeks’ less likely to anthropomorphize robotic agents.

ii. Effectance motivation

The first motivational factor that Epley et al. (2007) introduce in the scope of their theory is effectance motivation. It describes the desire to reduce the uncertainty about one’s environment and unknown agents and to be able to understand and make predictions about those. In a quite recent study of Waytz, Morewedge, Epley, Monteleone, Gao, and Cacioppo (2010) it has been shown that anthropomorphism enhances this ability, regardless of whether the assumptions one is making about the agent are correct or not. So instead of providing individuals with some sort of heuristic that increases the probability of formulating a correct explanation or prediction, effectance motivation rather increases the *confidence* one perceives in understanding and predicting. In this context anthropomorphism can be seen as a tool for having the feeling of understanding ‘the un-understandable’ (Hebb, 1946; Epley et al., 2007;). At the same time, showing strong effectance motivation is expected to result in an increase of the anthropomorphic response, whereas weak effectance motivation would lead to a decrease. The likelihood of having the desire to enhance the confidence about one's explanations and predictions can, according to Epley et al. (2007), be predicted by the occurrence of two dispositional determinants.

The two dispositional determinants of effectance motivation are suggested to be 'need for closure' and 'need for control'. Need for closure has been described as the individual tendency to desire *any* answer in order to avoid a state of ambiguity or uncertainty, when faced with a problem or decision (Webster and Kruglanski, 1994; Roets and Van Hiel, 2007, 2011). This desire is assumed to consist of two phases. The first phase is labeled *'seizing'* and consists of the individual tendency to urgently find an answer to escape ambiguity. An individual scoring high on this tendency thankfully accepts the first solution, or in this case model of agency, that is readily accessible. The second phase on the other hand is labeled '*freezing*', implying the tendency of rigidly sticking to this answer. This phase entails that once an explanation is found, the individual tends to keep it, even if alternative, contradictory explanations become available. In accordance to this, people high in need for closure have shown to exhibit primacy effects in forming impressions of stimuli and to rely on early information when making judgments about other people, instead of reconsidering their reasoning by integrating more recent information (Kruglanski & Webster, 1991). Based on these findings, Epley et al. (2007) expect people high in need for closure to rely also on readily available egocentric information and therefore to demonstrate a stronger anthropomorphic response, than people low in need for closure. But what inferences can we make about a 'geek's' tendency toward need for closure?

Assumptions can be made on the basis of research between the need for closure and cognitive motivation. According to Kruglanski, Peri, & Zakai (1991) the 'freezing' tendency co-occurs with a lowered motivation to search for information. Moreover Roets and Van Hiel (2011) have shown that the need for closure is significantly negative correlated with the need for cognition. Therefore, we infer that the 'geekism' (consisting of need for cognition and computer enthusiasm) will be negatively correlated with need for closure, too. This seems to be in accordance with common sense, since someone who enjoys effortful thinking, will not be content, not to mention desire the first available explanation, no matter if it is right or wrong. Due to these findings and assumptions so-called 'geeks' are expected to show low need for closure.

Research findings concerning the need for control and its role in anthropomorphism seem to be rather surprising. Epley et al. (2007) assume 'need for control' to be the second dispositional determinant of effectance motivation. They found the construct on the definition "the extent to which people generally are motivated to see themselves in control of the events in their lives" (Burger, 1992, p. 6, as cited in Epley et al., 2007). Based on research findings which suggest that those with a strong desire for control usually focus on intentions and desires in order to explain other's behavior (e.g. Burger & Hermans, 1988), they infer that those with a strong desire for control should rely more on egocentric representations and therefore demonstrate a higher anthropomorphic response. What is quite peculiar is the fact that the desire for control has been shown to correlate positively with the need for cognition (Thompson, Chaiken, & Hazelwood, 1993, as cited in Cacioppo et al. 1996) which is expected to result in a decreased likelihood of anthropomorphizing a nonhuman agent. In addition to the need for cognition, it has further been suggested that need for control itself could be part of ‘geekism’ (Schmettow and Passlick, 2013). If this is true, this should heighten the likelihood of people that tend to ‘geekism’ to anthropomorphize non-human agents.

This assumption conflicts with the suggestion that expertise in technology, high need for cognition and low need for closure should lead to an effortful correction process of the egocentric bias and subsequently result in the decrease of a ‘geek’s’ tendency to anthropomorphize. So, what can we expect to happen? In their theory of anthropomorphism of Epley et al. (2007) present a suggestion that might solve the conflict between those two assumptions.

Epley et al. (2007) point out that an interaction between the cognitive determinant ‘elicit knowledge’ and the motivational determinant ‘effectence motivation’ could very presumably result in a decrease in the tendency to anthropomorphize. They offer the possibility that, if a person feels uncertain about a non-human agent, effectance motivation is likely to enhance the use of alternative explanations about the agent’s behavior in order to make sense of it. That is, *if* those alternative explanations are available. If people with a tendency toward ‘geekism’ would be high in need for control and/or need for closure, the desire to be in control of and to urgently find an explanation about the functioning of a robotic agent would result in the reliance on the ‘geek’s’ expertise in technology instead of the reliance on egocentric representations. This in turn would lead to a decrease in the anthropomorphic response.

iii. Sociality

The second motivational determinant of the three-factor theory of anthropomorphism is sociality. Epley et al. (2007) describe it as the desire to establish social connections with other human beings. The idea is that, in absence of other people, sociality increases an anthropomorphic response towards a nonhuman agent, in order to achieve satisfaction of their wish for social connection. According to them, this increase is based on the assumption that people high on sociality (due to their lack of social satisfaction) (1) have a higher accessibility of egocentric representations and (2) demonstrate a higher tendency to actively search for sources of social connection in one’s environment. Epley et al. (2007) therefore suggest that individuals that perceive social disconnection are more likely to anthropomorphize a nonhuman agent, than people who feel socially fulfilled. Research on anthropomorphism of various nonhuman agents such as pets and socially interactive robots, has shown that anthropomorphism may indeed result in the satisfaction of the desire for social contact (e.g. Siegel, 1990).

The dispositional determinant that is expected to account for sociality is ‘chronic loneliness’. As we have seen earlier, social disconnection or chronic loneliness could not be identified as a feature of ‘geekism’. Due to the fact that the subculture of so-called ‘geeks’ provides a community of like-minded peers and even enjoys a gain in common popularity since the commercial success of the internet and related technical devices, we do not expect those individuals to be high in sociality (e.g. O’Brien, 2007; McArthur, 2008; Schmettow & Passlick, 2013). Concluding, once again we assume that people that tend to ‘geekism’ do not seem likely to anthropomorphize robotic agents.

1.4 *Concrete hypotheses*

In order to test the inferences about the likelihood to which people with a tendency towards geekism anthropomorphize a robotic agent, a number of concrete hypotheses was sat up. In preparation of an answer to this question, a number of specific sub-hypotheses on the concept of ‘geekism’ was formulated. First of all, we expect a positive association between computer enthusiasm and the participation in a technical study (a). Next, due to the fact that geekism is thought to consist of the tendency towards computer enthusiasm and need for cognition, we suggest that individuals with strong computer enthusiasm to show a strong need for cognition (b). Moreover we suggest a negative relation between computer enthusiasm and need for closure (c).

> *a) Individuals participating in a technical study,*
> *show stronger computer enthusiasm than individuals participating in a non-technical study.*
>
> *b) Individuals with strong computer enthusiasm,*
> *show a strong need for cognition.*
>
> *c) Individuals with strong computer enthusiasm,*
> *show a weak need for closure.*

The focus of this study lies of course on the extent to which people that tend to geekism anthropomorphize robotic agents. Expressed in concrete terms, our expectation with regard to this main research question is as follows:

> *d) Individuals that show strong computer enthusiasm and need for cognition, exhibit a weak anthropomorphic response.*

Next to this main hypothesis we aim to provide a scientific approach for a full investigation of the three-factor theory of anthropomorphism of Epley et al. (2007). Therefore we examined interaction effects between technology expertise and need for cognition (e) as well as between technology expertise and need for closure (f) on the extent to which one anthropomorphizes robotic agents. Based on the argumentation in section 1.3.ii, expertise has been approximated by the participation in a technical study, acting on the assumption that subjects participating in a technical bachelor's or master's program have more knowledge about technological devices than subjects participating in non-technical programs, such as psychology.

e) Technical students with a strong need for cognition, exhibit a weak anthropomorphic response.

f) Technical students with a strong need for closure, exhibit a weak anthropomorphic response.

2. Method

2.1 Sample

In order to test our hypotheses, we drew a sample of N = 60 participants. The sampled subjects were undergraduate students of the University of Twente, aged 19 to 29 (M = 22.25; SD = 1.962). The sample consisted of N_F = 34 female, N_{NL} = 21 Dutch and N_{DE} = 39 German students. Therefore all participants had a similar Western-European cultural background.

Table 1

Descriptives

	N	Mean	SD
Nationality	60		
German	39		
Dutch	21		
Gender	60		
Female	34		
Male	26		
Study	60		
Technical	21		
Other	39		
Age	59	22,25	1,962

The sampling of the subjects was done by a combination of convenience and snowball sampling (i.e. Dooley, 2009; Cohen, Manion and Morrison, 2011). To get access to people that potentially have a high tendency toward 'geekism', we approached students that are enrolled in technical studies, such as informatics, computer science and mechanical engineering. To obtain the necessary variance in the sample, students of non-technical faculties were added. Finally the sample consisted of N_T = 21 technical students and N_O = 39 students of non-technical programs, mainly psychology.

All bachelor psychology students in this study participated as part of their course fulfillment, while non-psychology students earned a financial reward. The participation was voluntary and did not take place under compulsion. At the beginning of the experimental each subject signed an informed consent, knowing that they may withdraw from the experiment whenever they wish to, without having to state a reason.

2.2 Material

In order to create an experimental condition under which the participants' extent of anthropomorphism could be assessed, twenty short video clips of moving robots were shown in random order. Each video clip had a length of 5 seconds and displayed only one robotic agent at a time, each conducting just one sort of movement. Possible sounds that came with the videos were removed, so that the videos could count as visual stimuli only. The videos have a resolution 1920x1080 (2.1 megapixel).

To gain variance, the amount to which the outer appearance and actions of the robots resembled human beings was diversified. The body of the robots differed from looking very mechanical with one or several wheels, no limbs, or even the shape of a disc, to the appearance of animals, such as a dog or a spider, to human-like, with having limbs, a head, hair or facial features. The movements that were shown varied from very simple and jerking forms of locomotion, such as rolling (9 videos), to more complex and smooth movements, like running, flying, balancing on rough ground or washing a window (11 videos). One of the videos showed a computer animated robot, while all the other 19 robots were existing technical devices.

2.3 Measures

i. Assessment of personality

In the scope of this study three different self-report instruments were used in order to identify the participant's computer enthusiasm, need for cognition and need for closure respectively. All of these questionnaires involve items in the shape of first-person statements. To judge those statements, a 7-point Likert scale was chosen, ranging from 'strongly disagree' (1), to 'strongly agree' (7). In the end the total score of each questionnaire was calculated. The items of all three scales were randomly mixed together to one questionnaire.

To assess to which extent the participants tend to computer enthusiasm the GEX was used. The GEX (standing for geekism, explicit) is a questionnaire that is composed of 15 items (Schmettow and Drees, 2014). The GEX shows an excellent psychometric quality with a test-retest reliability of .96 and a Chronbach's alpha of .96 and good discriminant validity towards the Need for Cognition Scale (r = .357) (Schmettow and Drees, 2014).

The *Need for Cognition Scale* has been included in the study due to the expectation of being a part of 'geekism' and in order to assess the dispositional determinant of the element ‘knowledge’ of the three-factor theory of anthropomorphism (Epley et al., 2007). The NCS is a unidimensional psychometric instrument that consists of 18 items and displays good reliability with a theta coefficient of .90 (Cacioppo, Petty and Kao, 1984).

In addition to the NCS, the *Need for Closure Scale* was used to measure one of the two dispositional determinants of yet another element of the three-factor theory of anthropomorphism: ‘effectance motivation’ (Epley et al., 2007). Originally developed by Webster and Kruglanski (1994), Roets and Van Hiel (2007) introduced a revised unidimensional version of the NFCS-R that consists of 41 items, divided into five subscales: discomfort with ambiguity, decisiveness, closed mindedness, preference for order and preference for predictability. The psychometric quality of the NFCS-R is acceptable due to an increased Cronbach’s alpha from .85 to .87 (sample 1) and from .82 to .86 (sample 2), an increased median inter-item correlation from .14 to .16 (sample 1) and from .12 to .16 (sample 2) and high, positive correlations between the revised decisiveness scale and all other facet scales.

ii. Explicit measure of anthropomorphism

Within this study, anthropomorphism was measured by the means of both, an explicit and an implicit instrument. In the first experimental condition (A), the extent to which the participants perceive the robots in the video clips as more or less human was explicitly measured by the ‘perceived humanness’ scale. Developed as an alternative to the Godspeed indices (Bartneck, Kulić, Croft and Zoghbi, 2009), the PH-scale is a self-report instrument for judging robotic agents based on Mori’s hypothetical graph of the ‘uncanny valley effect’ (Ho and MacDorman, 2010). Next to ‘perceived humanness’, other scales of this instrument are ‘eeriness’, ‘attractiveness’ and ‘warmth’.

The ‘perceived humanness’ scale contains 6 bipolar items. Each item is composed of a word pair, one word representing a robotic feature, and one word representing the apposed human-like feature. Examples of word pairs are ‘synthetic – real’ and ‘mechanical movement – biological movement’. To rate a robotic device on all six items, the subjects were asked to express their opinion on a semantic differential scale from 1 to 7. The use of a semantic differential scale instead of a Likert scale may effectively reduce acquiescence bias without diminishing the psychometric quality of the test (Friborg and Martinussen, 2006, retrieved in Bartneck et al., 2009). The ‘perceived humanness’ scale shows high internal reliability (Chronbach’s $\alpha = .92$) and exploratory factor analysis with no iterations revealed that it items all loaded on a single factor that accounts for 68.96% of its variance (Ho and MacDorman, 2010). Another benefit of the ‘uncanny valley’ devices is that its scales are not limited to robots, but includes computer-generated agents, so that the animated mars rover in the video sample does not bear any problems (Ho and MacDorman, 2010).

iii. Implicit measure of anthropomorphism

Self-report instruments such as Likert-scales have been shown to have their limitations. As Bartneck, et al. (2009) mentioned, questionnaires are based on the principle of retrograde reflection and thus prone to for instance social acceptable responses. Initial attitudes towards events or objects are supposedly only scarcely measured. Due to this limitation an implicit measurement has been added to assess the participant's extent of anthropomorphism (subsample B). The chosen implicit instrument is an adapted form of the Stroop priming task and is strongly based on the alteration which was used by Schmettow, Noordzij and Mundt (2013).

Originally set up by J.R. Stroop in 1935, the Stroop task is a very influential implicit measure in the field of cognitive processes, being used in at about 400 studies (MacLeod, 1991). In the original Stroop task the participants are exposed to a number of color names. These color names are themselves written in different colors. It is the task of the participants to respond the color of the font as fast as they can. In the incongruent version of the Stroop task, the font of the color names does not coincide with their meaning. When conducting this task, participants happen to have difficulties in naming the color of the font: the naming of the color and the reading of the word's meaning interfere, with the result that the reaction time of the participant increases. This increase in reaction time is called Stroop effect (Schmettow, Noordzij and Mundt, 2013) and entails the conclusion that reading is an automated process and is therefore difficult to suppress. This conclusion has led to a variation of the original Stroop task, which is called the *Stroop priming task*.

The Stroop priming task assesses the associations that a person has with a priming stimulus (Schmettow, Noordzij and Mundt, 2013). In this version of the Stroop task the target words are neither congruent, nor incongruent, but neutral. This means that words are chosen which have nothing to do with color, but are expected to be related to a certain stimulus. Whether a participant strongly associates a word with a certain stimulus (in other words: whether the association between target word and stimulus is strong or not), can be assessed through the reaction time of the participant: the more time the subject takes to name the correct font color, the stronger is the association between the stimulus and the word meaning. Crucial in this procedure is that the stimulus is presented right before the conduction of the Stroop task, which means that the participants have to be *primed* (Stanovich & West, 1983).

The functioning of the Stroop priming task is based on the construct of 'spreading activation', which in turn is part of the network theory as a fundamental memory retrieval mechanism (Collins and Loftus, 1975). This theory holds that concepts are represented in memory as nodes and learned relations between those nodes are represented as associative pathways. As soon as a concept in memory is activated by for instance an incoming stimulus, activation spreads along associative pathways to concepts (nodes) that are related to the initially activated one. The principle of spreading activation thus makes associated concepts more readily available for further processing. In case of the three-factor theory, Epley et al. (2007) suggest that a non-human agent is anthropomorphized due to the virtually automatic activation of egocentric biases. If this is true, it must be possible to demonstrate the association between agent and egocentric biases by the means of the Stroop priming task. The necessary stimulation or priming in order to activate anthropomorphic or non-anthropomorphic associations took place in the form of the earlier described videos.

Due to the fact that the robots in the videos were carrying out some sort of movement at the moment they were presented, 40 verbs were generated as target words for the Stroop priming task (Table 2). To be able to discriminate whether a participant perceives a robot as human-like or as robotic, we tried to find corresponding verbs, so that each humanlike action had a mechanical equivalent. Moreover 9 non-personal, agent-independent verbs were added. In the English version of the tasks, the verbs were presented in present progressive, so that they can be more easily distinguished from their respective substantive (i.e. ‘raining’ and ‘rain’). The target words of the Dutch and the German versions had the form of their infinitives, since these can be easily identified as verbs.

Table 2

Target words

Neutral	Human	System
raining	Movement	
mizzeling	walking	rolling
snowing	Energy	
dabbling	eating	recharging
overclouding	sleeping	shutting down
flashing	waking up	booting up
darken	recovering	repairing
thundering	sweating	airing
occurring	Cognition	
happening	remembering	loading
	forgetting	deleting
	thinking	computing
	speaking	paying back
	internalizing	saving
	erring	disfunctioning
	deciding	obeying
	unbridling	decoding
	discovering	detecting

2.4 Procedure

At the beginning of the procedure, each participant was placed in an isolated, quiet room supplied with a chair, desk and laptop. As soon as the subject was welcomed properly and sat down behind the computer, he or she was handed the informed consent and was given an explanation of the procedure.

All of the (N = 60) participants underwent the explicit measure of anthropomorphism (subsample A). In this condition the video clips were put into a Word Power Point presentation. As the participant pressed the right arrow key, he or she was exposed to one video clip and then got a few minutes time to judge the perceived robot on the 'perceived humanness' scale, until he or she pressed the right arrow key again. After the participants had finished the explicit measure they were given the questionnaire randomly composed of the items of the GEX, NCS and NFCS, which they were asked to fill in a few hours after the experimental procedure, in order to avoid possible priming effects and cognitive exhaustion

Before undergoing the explicit measure, the twenty participants that were assigned to the implicit measure (subsample B) were exposed to the Stroop priming task. Before starting the measure with the real primes and target words, the participants got a first idea of the workings of the Stroop priming task by running some practice trials. The task was to press the correct button as soon as the target word was visible. Reaction times were measured from the onset of the target word until the button on the keyboard was pressed. After finishing the practice trials, the experimental task started. During this task the participants were alternately exposed to one video clip and a series of 20 target words in random sequence. The Stroop priming task consisted of eight phases, each entailing all 20 video clips and separated by three brakes of two minutes. Subsequent to this procedure the twenty participants took part in the explicit measure (subsample A) described above. The reason for this sequence is again, that priming effects due to the explicit measure and the questionnaires was aimed to be avoided.

2.5 Data analysis

In order to investigate the sub-hypotheses whether computer enthusiasm, need for cognition and need for closure are associated with each other, Pearson correlations between the scores of the GEX, NCS, NFCS and the subscales of the NFCS were executed. The relationships between the scores of the personality scales and study type were estimated by the point-biserial correlation coefficient, which is used to compare a quantitative variable with a nominal or dichotomous variable (Di Lena, P., and Margara, L., 2010; Taylor, 1990).

To examine the hypotheses regarding the relationship between the predictors 'computer enthusiasm', 'need for cognition', 'need for closure' and the dependent variable perceived humanness (condition A) or Stroop-response time (condition B), we made use of a mixed-effects model. The Linear Mixed-effects model (LME) is a form of regression analysis which takes into account the variation that is not generalizable to the independent variables (Jiang, 2007). This is the case in repeated measures designs where same statistical units are measured repeatedly. In the scope of this study these units are the participants, items and primes, since we have multiple subjects, repeatedly responding to multiple primes and items. The resulting difficulty of this design is that multiple responses from the same subject cannot be taken as independent from each other. A classical solution to this problem is averaging over subjects for an item-analysis or averaging over items for a subject-analysis. This approach however, entails the disadvantage that either by-item variation or by-subject variation is ignored (Jiang, 2007). In contrast to classical statistic analysis, Linear mixed models are not prone to this disadvantage. Summed up, mixed-effects models have several benefits, compared to classical ANOVA: absent homogeneity of the regression slopes, dependency of the measurements and missing data are not problematical (Jiang, 2007).

As mentioned above, the three intercept random effects in this study are one subject-level random effect for the overall perceived humanness (PH) score of a participant and two material-level random effects, one for the overall tendency of items and one for the overall tendency of primes. The fixed effects in this study are the scores of the GEX, NCS and NFCS. Fixed factors are gender (male/female) and type of study (non-technical/technical). In accordance to the in 1.4 described hypotheses, main and interaction effects were investigated.

In order to investigate the psychometric quality of the used primes, items and the Perceived Humanness Scale, its scores were compared to the response time of the Stroop Priming task, also by a mixed effects model. The between-subjects factors are the scores of the GEX, NCS, NFCS and the perceived humanness scale. The word category of the targets (human-like, system-like and neutral), gender and study type are fixed factors. In the scope of all statistic analyses in this study a confidence level of p-value = 0,05 was maintained.

3. Results

In the scope of this study a total of 7196 perceived humanness (PH) responses was measured, distributed over twenty primes and six items per subject. Four subjects were excluded due to missing values. Mean response was a PH-score of 3.054 (SD = 0.282). The sample's average score for computer enthusiasm was M = -0.3323 (SD = 1.465). Subjects participating in a technical study scored significantly higher on the GEX than subjects participating in non-technical studies (t = -3.499, p = 0.001). Need for cognition ranged from -1.17 to 2.28 (M = 0.667, SD = 0.819) and did not significantly vary across the technical and non-technical students. In the case of need for closure on the other hand, technical students scored significantly lower than non-technical students (t = 2,475, p = 0.016). For an overview of all means, standard deviations and ranges of the personality scales, please consider table 3.

Table 3

Descriptive Statistics

	N	M	SD	Minimum	Maximum
Gex	60	-.3322	1.4648	-2.89	2.71
Technical studies	21	.4942	1.2719	-1.89	2.71
Other studies	39	-.7771	1.3782	-2.89	2.04
NCS	60	.6667	.8191	-1.17	2.28
Technical studies	21	.8968	.7130	-.33	2.28
Other studies	39	.5427	.8539	-1.17	2.28
NFCS	57	.1910	.5900	-1.16	1.64
Technical studies	19	-.0708	.5507	-1.16	.99
Other studies	38	.3219	.5715	-.72	1.64

In order to interpret the strength of the correlational coefficients the labeling system described by Dancey and Reidy (2007) was used, categorizing r values which are < .20 as weak, values < .50 as modest or moderate, values < .80 as strong and a value of 1.0 as perfect. For an overview of all correlation coefficients and p-values, please consider table 4.

Correlational analysis between computer enthusiasm and need for cognition has revealed a moderate positive correlation (r = 0.456, p < 0.001). As can be seen in figure 1, subjects high in need for cognition show a strong tendency toward computer enthusiasm. Secondly, a moderate negative correlation between need for cognition and need for closure was found (r = -0.273, p = 0.040). Individuals high in need for cognition, display low scores in need for closure (fig.2). Figure 3 displays that individuals high on need for closure by tendency show less computer enthusiasm. Yet, correlational analysis between these concepts did not yield a significant relation (r = -0.208, p = 0.120). Subdividing need for closure into the scores of the individual sub-scales, revealed a moderate negative correlation between computer enthusiasm and preference for order (r = -0.259, p = 0.049). The subscales decisiveness, closed mindedness and preference for order have been shown to be insignificantly negative related to computer enthusiasm (all p > 0.102), whereas discomfort with ambiguity and computer enthusiasm display an insignificant positive correlation (r = 0.024, p = 0.855). Further correlational analysis between the personality scales and study type disclosed significant correlations. In accordance with the results of the independent sample t-tests, the association between participation in a technical study and computer enthusiasm is moderately positive (r = .417, p = .001), whereas need for closure is modrately negative (r = -.317, p = .016) and need for cognition insignificantly positive correlated with the participation in a technical study.

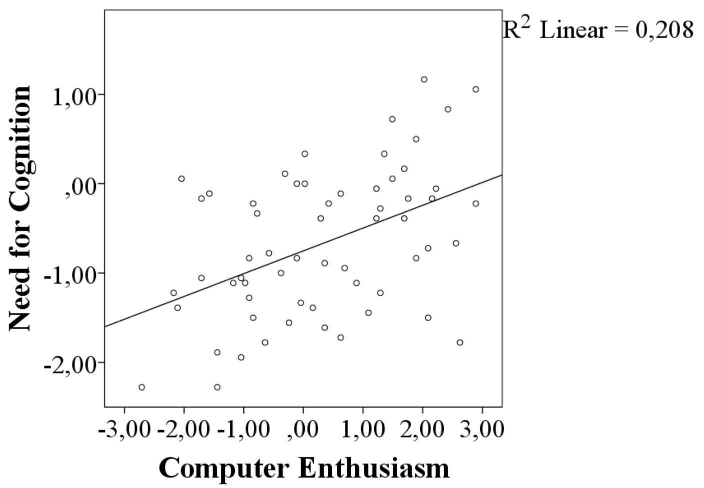

Fig. 2 Significant positive correlation between computer enthusiasm (x-axis) and need for cognition (y-axis).

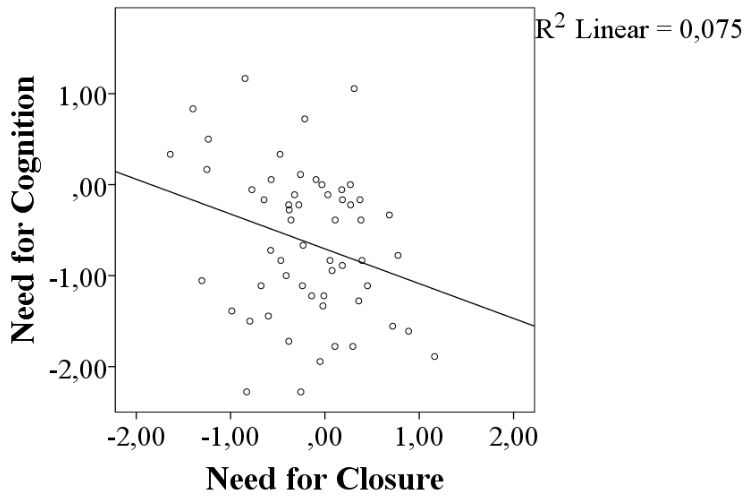

Fig. 3 Significant negative correlation between need for closure (x-axis) and need for cognition (y-axis).

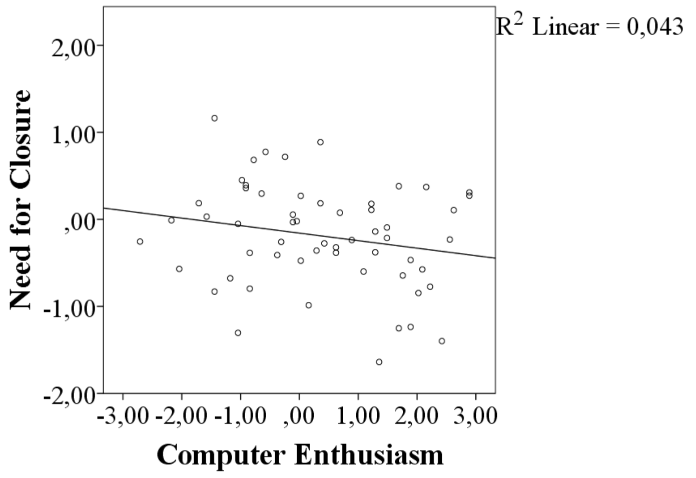

Fig. 4 Insignificant negative correlation between computer enthusiasm (x-axis) and need for closure (y-axis).

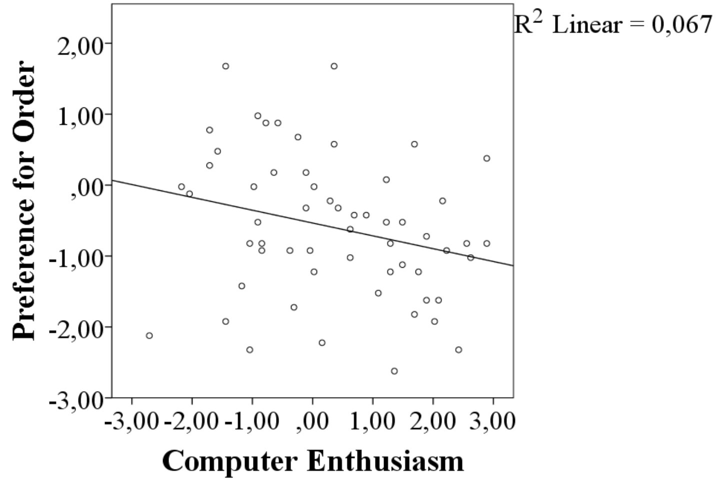

Fig. 5 Significant negative correlation between computer enthusiasm (x-axis) and need for closure sub-scale preference for order (y-axis).

Table 4

Correlations

	Gex	Technical study	NCS	NFCS	Closed Mindedness	Decisiveness	Discomfort with Ambiguity	Preference for Order	Preference for Predictability
Gex	---								
Technical study	.417** .001 60	---							
NCS	.456** ,000 60	.208 .111 60	---						
NFCS	-.208 .120 57	-.317* .016 57	-.273* .040 57	---					
Closed Mindedness	-.213 .102 60	.059 .652 60	-.442** .000 60	.442** .001 57	---				
Decisiveness	-.108 .411 60	-.380** .003 60	.021 .876 60	.672** ,000 57	.207 .113 60	---			
Discomfort with Ambiguity	.024 .855 60	-.222 .088 60	-.003 .983 60	.688** .000 57	.116 .379 60	.361** .005 60	---		
Preference for Order	-.259* .049 58	-.237 .073 58	-.162 .225 58	.848** .000 57	.286* .030 58	.497** .000 58	.548** .000 58	---	
Preference for Predictability	-.163 .218 59	-.245 .061 59	-.348** .007 59	.710** ,000 57	.154 .246 59	.232 .077 59	.397** .002 59	.519** .000 57	---

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The mixed-effects regression analysis between the assumed predictors computer enthusiasm, need for cognition and need for closure of the dependent variable perceived humanness yields no statistically significant results (for an overview see table 5). Whereas the size of the coefficients of computer enthusiasm and need for cognition are practically zero (β = .048912 and β = -.041976 respectively), the coefficient of need for closure (β = .420042) seems to be of some practical relevance. Yet, none of these estimations is beyond chance level. With regard to the fixed factors study type and gender, only study type could be shown to have a coefficient of practical value (β = .420878). But also these effects were statistically insignificant.

Table 5

Fixed effects on perceived humanness

			95% Confidence Interval	
Source	Coefficient	P	Lower Bound	Upper Bound
Main effects				
Intercept	3.3228	.000	2.5705	4.0751
Gender (male)	-.0359	.874	-.4875	.4157
Type of study (technical)	.4209	.169	-.1858	1.0275
Gex	.0489	.965	-.2472	.3450
NCS	-.0420	.871	-.5003	.4163
NFCS	.4200	.158	-.1826	1.0226
Interaction effects				
Gex by NCS	-.0781	.316	-.2334	.0772
Gex by NFCS	.1852	.124	-.0528	.4233
Gex by Type of study (technical)	.0891	.579	-.2320	.4102
NCS by Type of study (technical)	-.1273	.668	-.7207	.4660
NFCS by Type of study (technical)	.3152	.388	-.4135	1.0438

Random effects

	Coefficient	SD
Subject	.3579	.0788
Item	.0708	.0459
Prime	.9428	.3078

The main hypotheses whether individuals that tend to geekism, show a higher anthropomorphic response, is expressed in an interaction effect between computer enthusiasm and need for cognition on perceived humanness. This interaction effect has been shown to be practically zero (β = -.078097) and not beyond chance level. Although displaying a quite relevant increase in the anthropomorphic response (β = .315158), an interaction effect between technical study and need for closure was not statistically significant. In addition, a relevant coefficient (β = -.127349) of an interaction effect between technical study and need for cognition, indicated a decrease in the anthropomorphic response, but as well, not beyond chance level. Finally, no relevant or statistically significant interaction effect between computer enthusiasm and study type on the perceived humanness could be found (β = .089100).

Table 6

Fixed effects on Stroop response time

	Coefficients	P	95% Confidence Interval Lower Bound	Upper Bound
Main effects				
Intercept	.4289	.000	.2185	.6394
Gender (male)	.2165	.079	.0152	.4178
Gex	-.0326	.764	-.1546	.0893
NCS	-.0386	.835	-.1732	.0960
NFCS	.2578	.286	.0136	.5020
Type of study (technical)	-.0660	.262	-.2702	.1381
Perceived humanness	-.0007	.583	-.0095	.0110
Word category (human)	-.0179	.215	-.0600	.0242
Word category (neutral)	.0304	.215	-.0172	.0851
Interaction effects				
Gex by Word category (human)	-.0028	.470	-.0397	.0340
Gex by Word category (neutral)	.0003	.479	-.0444	.0449
NCS by Word category (human)	.0200	.549	-.0205	.0606
NCS by Word category (neutral)	.0466	.549	-.0026	.0957
NFCS by Word category (human)	.0388	.822	-.0134	.0910
NFCS by Word category (neutral)	.0525	.822	-.0100	.1150
Type of Study by Word category (human)	.0023	.253	-.0604	.0650
Type of Study by Word category (neutral)	-.0571	.253	-.1327	.0185
Gex by NCS by Word category (human)	.1051	.449	-.0544	.2647
Gex by NCS by Word category (neutral)	.1206	.449	-.0409	.2821
Gex by NCS by Word category (system)	.1082	.449	-.0513	.2678
Gex by Type of study (technical) by Word category (human)	-.0594	.757	-.5029	. 3841
Gex by Type of study (technical) by Word category (neutral)	-.0935	.757	-.5665	.3207
Gex by Type of study (technical) by Word category (system)	-.1229	.757	-.5665	-.3207
NCS by Type of study (technical) by Word category (human)	-.1781	.545	-.5102	.1540
NCS by Type of study (technical) by Word category (neutral)	-.1400	.545	-.4759	.1958

NCS by Type of study (technical) by Word category (system)	.1908	.545	-.5228	.1411
NFCS by Type of study (technical) by Word category (human)	.2038	.444	-.4826	.8413
NFCS by Type of study (technical) by Word category (neutral)	.1793	.444	-.4826	.8413
NFCS by Type of study (technical) by Word category (system)	.0677	.444	-.5883	.7236
Perceived humanness by Word Category (human)	.0040	.585	-.0087	.0167
Perceived humanness by Word Category (neutral)	-.0126	.585	-.0281	.0029

Random effects

	Coefficient	SD
Subject	.0105	.0051
Target word	.0001	.0002
Prime	.0003	.0002

Within mixed-effects regression analysis of the relation between the Stroop response time and the personality constructs, no statistically significant results could be found with regard to the hypotheses. Hypotheses (d) was tested by the means of a three-way interaction between computer enthusiasm, need for cognition and word category, while hypotheses (e) was tested by a three-way interaction between study type, need for closure and word category. The analysis yielded few if any coefficients of practical value and no statistically significant main effects of computer enthusiasm, need for cognition, need for closure and study type. The same holds for any interaction effects between these variables. For an overview of all regression coefficients, p-values and confidence intervals, please consider table 6.

By comparing the response times of the Stroop Priming task with the responses on the perceived humanness scale, we estimated the psychometric quality of the primes and the target words. Correlational analysis between the response time and the PH-score, resulted in a weak negative correlation for neutral words ($r = -0.143$, $p < 0.001$) and insignificant negative correlations for system ($r = -0.042$, $p = 0.142$) and human words ($r = -0.011$, $p = 0.689$). By means of mixed-effects regression analysis, no interaction effect of word category (human, neutral, system) and perceived humanness on response time could be found (see table 5). Thus both could not be shown to be of any predictive value for the response time on the Stroop priming task. The estimates of the random effects demonstrate that the variance in response times was stronger per subject ($\beta = .010496$), than per target word ($\beta = .000114$) or prime ($\beta = .000264$). The estimates indicate that the variation of the response time depends more on the variation between the subjects, than on the variation between the primes and the target words.

4. Conclusion and Discussion

4.1 Conclusion

In the scope of the explicit and implicit measure of anthropomorphism it could not be shown that individuals that tend to geekism exhibit a weaker anthropomorphic response than individuals who do not. Neither computer enthusiasm, nor need for cognition – whether isolated or in interaction – could be found to predict a decrease or increase in the extent to which the individuals anthropomorphized robotic agents. In addition, contrary to the three-factor theory of anthropomorphism of Epley et al. (2007) the assumption, that the presence of technology expert knowledge would result in a weaker anthropomorphic response, whether in interaction with or independent from need for closure, could not be confirmed.

With regard to the investigation of computer enthusiasm and possibly related concepts, two of three hypotheses could be confirmed. First of all and in accordance with common sense, the expectation could be approved that students participating in a technical study show high computer enthusiasm, and therefore enjoy the engagement in technology and its underlying systems more than non-technical students. Furthermore, a moderately positive correlation between computer enthusiasm and need for cognition supports the assumption that these two concepts form the basic components of ‘geekism’ (Schmettow and Mundt, 2012; Schmettow, Noordzij and Mundt, 2013). In line with research by Roets and Van Hiel (2011) high need for cognition has been shown to be related to a low need for closure, indicating that individuals who like to engage in effortful thinking are not likely to accept and keep the first accessible explanation in order to understand the ‘un-understandable’. However, this does not seem to apply generally to individuals with high computer enthusiasm, which is why we cannot conclude that so-called geeks differ from other people if it comes to the need for closure. Yet, individuals with computer enthusiasm, showed a lower tendency toward preference for order, one of the sub-scales of the need for closure scale, meaning that they attach less importance to a neat surrounding and well-structured schedule. This in turn could not be found for individuals high on need for cognition. These findings also support the assumption that need for cognition and computer enthusiasm are closely related, but distinct from each other, forming the concept of ‘geekism’. The need for closure does not seem to be an additional component of this concept.

As we have seen the assumption that so-called geeks tend to anthropomorphize less than other people – because of the presence of technological models of agency, and the enhanced likelihood to activate and integrate these due to a high need for cognition and a low or absent need for closure – could not be confirmed. This lack of any significant results with regard to these inferences raises several questions.

4.2 Discussion

Before engaging in a detailed discussion about the three-factor theory of anthropomorphism and the implicit as well as the explicit measure of the anthropomorphic response, it must be mentioned that the absence of the third determinant of the three-factor theory of anthropomorphism might be responsible for the lack of any statistically significant results. Sociality, the supposed second motivational factor of anthropomorphism, has not been controlled in this study. This could be significant, because Epley et al. (2007) have suggested an additional interaction effect between sociality and expertise, expecting sociality to rule out the effect of expertise and resulting in a higher anthropomorphic response. As an example for this effect, they describe a computer technician who obviously has a lot of expert agent knowledge about computers, who would anthropomorphize his computer and treat it as a friend, in case he has strong feelings of loneliness and is longing for social contact. Although results of the interview studies of O'Brien (2007) and Schmettow and Passlick (2013) suggest that chronic loneliness and low social skills are not necessarily generalizable to the concept of 'geekism', a relation has not been investigated yet. Still, the possibility exists that some of the subjects participating in this study were experiencing feelings of loneliness at the time of the investigation, regardless of whether they tend to geekism or not. Therefore we advise to include sociality to all future studies that are based on the three-factor theory of anthropomorphism. Yet, some other explanations might account for the lack of any statistically significant effects.

First of all, the results of this study shed a skeptical light on the three-factor theory of anthropomorphism of Epley et al. (2007). Contrary to their expectations, in both measures the extent of expertise knowledge, need for cognition and need for closure was not able to predict the anthropomorphic responses of the participants.

The critical focus lies especially on the activation and integration of models of agency. As explained in section 1.3.i., this is expected to take place as part of an inductive process. If confronted with a non-human but very humanlike agent, Epley et al. (2007) assume that the activation of egocentric representations takes place virtually automatically, due to their high accessibility and rich detail. As a consequence, they claim, the agent is anthropomorphized. On the other hand they suggest that, non-anthropomorphic models of agency could be co-activated due to thorough experience with and expertise about the agent. The idea of activating egocentric or alternative representations seems to be in line with the network theory and the construct of 'spreading activation' (Collins and Loftus, 1975). Because of this accordance the Stroop priming task, which is thought to function on the basis of 'spreading activation', should have been able to test whether this part of the inductive process is actually taking place or not. Yet, neither associations between robotic agents and human-like target words (which would account for the activation of egocentric representations) nor system-like target words (which would account for the activation of alternative models of agency) could be found. At first sight this might suggest that the assumption of Epley et al. (2007) that an anthropomorphic response is based on an automatic activation of egocentric representations is not correct.

However, the Stroop priming task is not able to detect whether the activation of egocentric representations is automatic or not. The Stroop priming task operates on a semantic processing level, using verbal stimuli in order to detect associations with preceding primes (Roelofs, J., Peters, M., Fassaert, T., & Vlaeyen, J., 2005). To figure out whether the activation of egocentric representations depends on automatic or semantic processing, one could use a setting in which the presentation times of robotic agents is manipulated. In this kind of experimental setting, a participant is exposed to a certain amount auf primes; in this case videos or pictures of robotic agents. In the beginning of the experiment, these primes are presented at a pace that does not allow conscious visual perception (Damian, 2001). With each completed trial, the presentation time increases, until the primes are eventually presented with a duration that allows thorough evaluation. Subsequent to each prime, the participant will be asked to fill in an explicit measure that assesses his or her anthropomorphic response. If egocentric representations really are automatically activated, the displayed response at the subliminal exposure may not statistically differ from the response at long duration times: in both cases an anthropomorphic response must be indicated (based on explanations in Damian, 2001). If, however, the responses on the explicit measure of anthropomorphism differ significantly, it cannot be concluded that the activation of egocentric representations is taking place on an automatic processing level. Next to the assumption of Epley et al. (2007) that an anthropomorphic response relies on the *automatic* activation of egocentric representations, the suggestion that those egocentric representations can be *corrected* by expert knowledge, may be able to test by the means of presentation time manipulation. This will be explained in the following.

Epley et al. (2007) stated that the correction of the egocentric bias, and a resulting reduction of the anthropomorphic response, might take place only in case of completing the application phase of the inductive process. During this phase, it is 'decided' whether co-activated alternative models of agency are integrated to the inferences about the agent or not. This 'decision' depends on the engagement in an effortful reasoning process, which, in turn, is the result of the need for cognition (Epley et al., 2007). The reason why effortful processing is thought to be necessary in order to alter one's inferences about the non-human agent, is based on the assumption that any alternative representations are too simple and difficult to access, compared to the dominant egocentric bias and are therefore not able to compete with it on an automatic processing level (Epley et al. 2007). The findings that the correction of initial inferences about unknown agents results in a reduction of egocentric biases (Epley et al., 2004) and that people are more likely to correct prejudices if they are high on need for cognition (Cacioppo et al., 1996), support the assumption of Epley et al. (2007) that the alternative representations might prevail over the egocentric bias through effortful processing. Therefore it is possible that the amount of time given to the participants in the Stroop priming task was not sufficient to facilitate a decrease in the anthropomorphic response, since the participants could not engage in an effortful thinking process. If the first assumption, that egocentric biases are taking place automatically, could be confirmed by the manipulation of presentation times (as described above), we may suggest that people with expertise about robots, will display a lower anthropomorphic response when exposed to long presentation times than when exposed to short or subliminal ones. Moreover, in order to achieve an accurate assessment, we advice to operationalize 'expertise' less broadly than has been done in the scope of this study. The used sample consisted of students from varying technical studies, such as mechanical engineering, technical informatics, computer science, biomedical technology, technical medicine, technical mathematics and electrical engineering. It is clear that not all of these students may have been equally exposed to robots and their functioning and therefore may strongly differ in their level of expertise. It is likely however, that explicit, thorough experience with robotic agents is necessary in order to create mental representations that are able to compete with egocentric biases.

Yet, even if the Stroop priming task was not able to detect any effects of the psychological determinants on the anthropomorphic response, it is still remarkable that neither the explicit measure of anthropomorphism did. Next to the assumption that the three-factor theory of anthropomorphism is completely wrong and not able to predict anthropomorphic responses, there are some reasons to assume that the use of the perceived humanness scale was erroneous. First of all, the semantic differential method as used for the perceived humanness scale, goes with the disadvantage that the meaning of adjectives chosen as anchors may be interpreted differently by individuals (Bartneck et al., 2009). Some subjects for instance, might interpret the feature 'without definite lifespan' as applicable to robots as well as to human beings. During the debriefing this has actually been reported by some participants: They found robots to be equally prone to a definite lifespan than human beings.

Moreover some participants in this study rated a robot relatively high on the perceived humanness scale, because they were delighted by its construction and functioning. At the same time they reported not to believe that the perceived robot was an independently acting agent, but saw it purely as a machine, lacking anything like character traits, let alone feelings. In contrast, several studies have shown that there is more to anthropomorphism than the description of an agent's behavior or outer appearance, but that anthropomorphism encompasses the attribution of character traits and mental and emotional states (e.i Barret and Keil, 1996; Hergenhahn, 2009). Thus, although good psychometric quality of the scale has been reported (Ho and MacDorman, 2010), the items of the perceived humanness scale seem to be a rather objective measure of how human-like a robotic agent appears with regard to its features and functions, than a 'proper' measure of anthropomorphism.

The key to an effective measure of anthropomorphism seems the inclusion of an affective component. As Mori (1970) suggested, the extent to which one perceives an agent as humanlike, is accompanied by an emotional response that varies from 'likable' to 'unpleasant' or even 'threatening'. As 'being in the Uncanny Valley', Mori (1970) described the state in which agents that are perceived as very humanlike (with regard to their outer appearance and functioning) evoke strongly negative feelings of unfamiliarity or even eeriness. Less perfect agents or agents that are even (almost) perfectly humanlike, on the other hand, are expected to produce a feeling of familiarity or even affection (Fig. 6). Even if there still exists controversy with regard to the Uncanny Valley, and no clear evidence could be delivered in order to explain its underlying mechanism, the importance of affect in anthropomorphism has been indicated in several studies: Misselhorn (2009) for instance, showed that within the entertainment industry the facilitation of robots with faces evoked strong emotional responses and enhanced the feeling of being entertained (one might think of Pixar's Wall-E). Moreover, Slater (2006) indicated that human beings have feelings of empathy when virtual avatars were threatened or hurt, although they were aware of the fact that these persons were animated and did not really feel pain.

Even more importantly, research suggests that the emotional responses are not a mere by-product of the human-likeness of an agent: It has been shown that even simple geometric forms (Heider & Simmel, 1944) and other simple computer animations (Rickenberg and Reeves, 2009) that do not share any bodily features with human beings, can evoke the attribution of character traits, emotions and intentions as well as feelings of empathy towards the perceived agents. Misselhorn (2009) infers that, due to this, the occurrence of anthropomorphism can possibly only slightly be moderated by knowledge about the agent, since it is immediately recognizable that the geometric forms are only drawings. This suggestion either supports the idea of Epley et al. (2007) that alternative models of agency are only applied through a process of effortful thinking, or contradicts this assumption, by stating that egocentric biases cannot be overcome by alternative knowledge about the agent. This again, asks for a thorough investigation of the inductive process, as expected by Epley et al. (2007).

Anyway, all these studies suggest that emotion-inspired mechanisms of robots have a strong influence on the way they are perceived by human beings. Due to the influential role of affect in the concept of anthropomorphism, Ho and MacDorman (2010) included the affective components 'eeriness', 'attractiveness' and 'warmth' in the revised Godspeed indices, which seem to be necessary in order to investigate an anthropomorphic response and not the mere 'human-likeness' of a robotic agent. Therefore we suggest using all scales, when a person's anthropomorphic response shall be assessed. In addition, videos of robots chosen as primes should include more than mere movements, but behavior that expresses some kind of emotion, in order to enhance the likelihood of ascribing characteristic humanlike features to the agent.

4.5 Summary

In the scope of this study it could not be shown that so-called 'geeks' tend to anthropomorphize to a different extent than other people. Moreover no evidence could be found in favor of the three-factor theory of anthropomorphism. In order to investigate these topics in future studies, a few points should be taken into account. First of all, sociality should be added to the research model in order to control for possible interaction effects. Secondly, we advice to use the manipulation of presentation times in order to investigate the activation and integration of egocentric and alternative models of agency. Finally, due to the fact that anthropomorphism seems to be related to emotional responses toward the anthropomorphized agents, one should make sure to include an affective component to the explicit assessment of anthropomorphism.

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6. Appendix

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Gex	1	39	-,7771	1,37821	,22069
	2	21	,4942	1,27190	,27755

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		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
Gex	Equal variances assumed	,714	,402	-3,499	58
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Independent Samples Test					
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					Lower
Gex	Equal variances assumed	,001	-1,27131	,36337	-1,99867
	Equal variances not assumed	,001	-1,27131	,35460	-1,98594

Independent Samples Test		
		t-test for Equality of Means
		95% Confidence Interval of the Difference
		Upper
Gex	Equal variances assumed	-,54394
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[DataSet6]

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	2	21	,8968	,71304	,15560

Independent Samples Test					
		Levene's Test for Equality of Variances		t-test for Equality of Means	
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NCS	Equal variances assumed	1,346	,251	-1,619	58

	Equal variances not assumed			-1,709	47,809

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NCS	Equal variances assumed	,111	-,35409	,21872	-,79191
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		Upper
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	File	
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	Cases Used	Statistics for each analysis are based on the cases with no missing or out-of-range data for any variable in the analysis.
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Group Statistics

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Independent Samples Test

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NCCR	Equal variances assumed	,017	,896	2,475	55
	Equal variances not assumed			2,506	37,335

Independent Samples Test

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					Lower
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	Equal variances not assumed	,017	,39272	,15670	,07530

Independent Samples Test		
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		95% Confidence Interval of the Difference
		Upper
NCCR	Equal variances assumed	,71073
	Equal variances not assumed	,71013

SORT CASES BY TypeofStudy.

SPLIT FILE SEPARATE BY TypeofStudy.

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Descriptives

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	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Gex NCS NCCR /STATISTICS=MEAN STDDEV MIN MAX.
Resources	Processor Time	00:00:00,00
	Elapsed Time	00:00:00,04

[DataSet6]

StudyType = 1

Descriptive Statistics[a]					
	N	Minimum	Maximum	Mean	Std. Deviation
Gex	39	-2,89	2,04	-,7771	1,37821
NCS	39	-1,17	2,28	,5427	,85389
NCCR	38	-,72	1,64	,3219	,57146
Valid N (listwise)	38				

a. StudyType = 1

StudyType = 2

Descriptive Statistics[a]					
	N	Minimum	Maximum	Mean	Std. Deviation
Gex	21	-1,89	2,71	,4942	1,27190
NCS	21	-,33	2,28	,8968	,71304
NCCR	19	-1,16	,99	-,0708	,55071
Valid N (listwise)	19				

a. StudyType = 2

```
SPLIT FILE OFF.

DESCRIPTIVES VARIABLES=Gex NCS NCCR

/STATISTICS=MEAN STDDEV MIN MAX.
```

Descriptives

Notes	
Output Created	27-JUN-2014 17:11:19
Comments	

Input	Active Dataset	DataSet6
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	60
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Gex NCS NCCR /STATISTICS=MEAN STDDEV MIN MAX.
Resources	Processor Time	00:00:00,00
	Elapsed Time	00:00:00,00

[DataSet6]

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Gex	60	-2,89	2,71	-,3322	1,46481
NCS	60	-1,17	2,28	,6667	,81912
NCCR	57	-1,16	1,64	,1910	,59003
Valid N (listwise)	57				

GET

FILE='C:\Users\Lea\dwhelper\Desktop\studie\3\BA-these\Exp\DATA\Main.sav'.

DATASET NAME DataSet1 WINDOW=FRONT.

MIXED response BY Gender TypeofStudy WITH Gex NCS NCCR

/CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1) SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)

/FIXED=Gender TypeofStudy Gex NCS NCCR Gex*NCS Gex*NCCR TypeofStudy*Gex TypeofStudy*NCS TypeofStudy*NCCR | SSTYPE(3)

/METHOD=REML

/PRINT=SOLUTION

/RANDOM=INTERCEPT | SUBJECT(participant) COVTYPE(VC)

/RANDOM=INTERCEPT | SUBJECT(prime) COVTYPE(VC)

/RANDOM=INTERCEPT | SUBJECT(item) COVTYPE(VC).

Mixed Model Analysis

Notes		
Output Created		01-JUL-2014 13:22:22
Comments		
Input	Data	C:\Users\Lea\dwhelper\Desktop\studie\3\BA-these\Exp\DATA\Main.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	7200
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the model.

Notes	
Syntax	MIXED response BY Gender TypeofStudy WITH Gex NCS NCCR /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1) SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE) /FIXED=Gender TypeofStudy Gex NCS NCCR Gex*NCS Gex*NCCR TypeofStudy*Gex

		TypeofStudy*NCS TypeofStudy*NCCR | SSTYPE(3) /METHOD=REML /PRINT=SOLUTION /RANDOM=INTERCEPT | SUBJECT(participant) COVTYPE(VC) /RANDOM=INTERCEPT | SUBJECT(prime) COVTYPE(VC) /RANDOM=INTERCEPT | SUBJECT(item) COVTYPE(VC).
Resources	Processor Time	00:00:00,23
	Elapsed Time	00:00:00,28

[DataSet1] C:\Users\Lea\dwhelper\Desktop\studie\3\BA-these\Exp\DATA\Main.sav

Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters
Fixed Effects	Intercept	1		1
	Gender	2		1
	TypeofStudy	2		1
	Gex	1		1
	NCS	1		1
	NCCR	1		1
	Gex * NCS	1		1
	Gex * NCCR	1		1
	TypeofStudy * Gex	2		1
	TypeofStudy * NCS	2		1
	TypeofStudy * NCCR	2		1
Random Effects	Intercept[b]	1	Variance Components	1
	Intercept[b]	1	Variance Components	1
	Intercept[b]	1	Variance Components	1
Residual				1
Total		19		15

Model Dimension[a]		
		Subject Variables
Fixed Effects	Intercept	
	Gender	
	TypeofStudy	
	Gex	
	NCS	
	NCCR	
	Gex * NCS	
	Gex * NCCR	
	TypeofStudy * Gex	
	TypeofStudy * NCS	
	TypeofStudy * NCCR	
Random Effects	Intercept[b]	participant
	Intercept[b]	prime
	Intercept[b]	item
Residual		
Total		

a. Dependent Variable: response.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]	
-2 Restricted Log Likelihood	23790,407
Akaike's Information Criterion (AIC)	23798,407
Hurvich and Tsai's Criterion (AICC)	23798,413
Bozdogan's Criterion (CAIC)	23829,649
Schwarz's Bayesian Criterion (BIC)	23825,649

The information criteria are displayed in smaller-is-better forms.[a]

a. Dependent Variable: response.

Fixed Effects

Type III Tests of Fixed Effects[a]				
Source	Numerator df	Denominator df	F	Sig.
Intercept	1	40,463	120,032	,000
Gender	1	45,002	,026	,874
TypeofStudy	1	44,999	1,953	,169
Gex	1	44,999	,002	,965
NCS	1	44,999	,027	,871
NCCR	1	45,000	2,057	,158
Gex * NCS	1	45,000	1,026	,316
Gex * NCCR	1	45,004	2,457	,124
TypeofStudy * Gex	1	44,999	,312	,579
TypeofStudy * NCS	1	45,000	,187	,668
TypeofStudy * NCCR	1	45,002	,759	,388

a. Dependent Variable: response.

Estimates of Fixed Effects[a]						
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	3,322795	,376912	67,013	8,816	,000	2,570479
[Gender=1]	-,035903	,224242	45,002	-,160	,874	-,487548
[Gender=2]	0[b]	0	.	.	.	.
[TypeofStudy=1]	-,420878	,301193	44,999	-1,397	,169	-1,027512
[TypeofStudy=2]	0[b]	0	.	.	.	.
Gex	,048912	,146997	44,999	,333	,741	-,247155
NCS	-,041976	,227533	44,999	-,184	,854	-,500251
NCCR	,420042	,299193	44,999	1,404	,167	-,182563
Gex * NCS	-,078097	,077096	45,000	-1,013	,316	-,233377
Gex * NCCR	,185246	,118169	45,004	1,568	,124	-,052758
[TypeofStudy=1] * Gex	-,089100	,159447	44,999	-,559	,579	-,410242
[TypeofStudy=2] * Gex	0[b]	0	.	.	.	.
[TypeofStudy=1] * NCS	,127349	,294599	45,000	,432	,668	-,466005
[TypeofStudy=2] * NCS	0[b]	0	.	.	.	.
[TypeofStudy=1] * NCCR	-,315158	,361789	45,002	-,871	,388	-1,043837
[TypeofStudy=2] * NCCR	0[b]	0	.	.	.	.

Estimates of Fixed Effects[a]	
Parameter	95% Confidence Interval
	Upper Bound
Intercept	4,075111
[Gender=1]	,415742
[Gender=2]	.[b]
[TypeofStudy=1]	,185755
[TypeofStudy=2]	.[b]
Gex	,344979
NCS	,416299
NCCR	1,022648
Gex * NCS	,077182
Gex * NCCR	,423250
[TypeofStudy=1] * Gex	,232043
[TypeofStudy=2] * Gex	.[b]
[TypeofStudy=1] * NCS	,720703
[TypeofStudy=2] * NCS	.[b]
[TypeofStudy=1] * NCCR	,413522
[TypeofStudy=2] * NCCR	.[b]

a. Dependent Variable: response.

b. This parameter is set to zero because it is redundant.

Covariance Parameters

Estimates of Covariance Parameters[a]			
Parameter		Estimate	Std. Error
Residual		1,933231	,033562
Intercept [subject = participant]	Variance	,357883	,078847
Intercept [subject = prime]	Variance	,942792	,307751
Intercept [subject = item]	Variance	,070830	,045889

a. Dependent Variable: response.

GET

STATA FILE='W:\Groups\BA Electric sheep\Data\D2.dta'.

DATASET NAME DataSet1 WINDOW=FRONT.

RECODE Study (1=2) (2=2) (3=2) (4=2) (5=2) (6=1) (7=2) (8=1) (9=2) (10=1) (11=2) (12=1) (13=2) (14=2) (15=2) (16=2) (17=2) (18=2) INTO TypeOfStudy.

VARIABLE LABELS TypeOfStudy 'StudyType'.

EXECUTE.

MIXED RT BY Gender wordCat TypeOfStudy WITH Gex NCS NCCR score

/CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1) SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)

/FIXED=Gender wordCat TypeOfStudy Gex NCS NCCR score wordCat*TypeOfStudy wordCat*Gex wordCat*NCS wordCat*NCCR wordCat*score wordCat*TypeOfStudy*Gex wordCat*TypeOfStudy*NCS wordCat*TypeOfStudy*NCCR | SSTYPE(3)

/METHOD=REML

/PRINT=SOLUTION

/RANDOM=INTERCEPT | SUBJECT(participant) COVTYPE(VC)

/RANDOM=INTERCEPT | SUBJECT(targetWord) COVTYPE(VC)

/RANDOM=INTERCEPT | SUBJECT(prime) COVTYPE(VC).

Mixed Model Analysis

Notes		
Output Created		01-JUL-2014 18:36:38
Comments		
Input	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	3226
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the model.

Notes		
Syntax		MIXED RT BY Gender wordCat TypeOfStudy WITH Gex NCS NCCR score /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1) SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE) /FIXED=Gender wordCat TypeOfStudy Gex NCS NCCR score wordCat*TypeOfStudy wordCat*Gex wordCat*NCS wordCat*NCCR wordCat*score wordCat*TypeOfStudy*Gex wordCat*TypeOfStudy*NCS wordCat*TypeOfStudy*NCCR | SSTYPE(3) /METHOD=REML /PRINT=SOLUTION /RANDOM=INTERCEPT | SUBJECT(participant) COVTYPE(VC) /RANDOM=INTERCEPT | SUBJECT(targetWord) COVTYPE(VC) /RANDOM=INTERCEPT | SUBJECT(prime) COVTYPE(VC).
Resources	Processor Time	00:00:00,98
	Elapsed Time	00:00:01,00

[DataSet1]

Model Dimension[a]				
		Number of Levels	Covariance Structure	Number of Parameters
Fixed Effects	Intercept	1		1
	Gender	2		1
	wordCat	3		2

	TypeOfStudy	2		1
	Gex	1		1
	NCS	1		1
	NCCR	1		1
	score	1		1
	wordCat * TypeOfStudy	6		2
	wordCat * Gex	3		2
	wordCat * NCS	3		2
	wordCat * NCCR	3		2
	wordCat * score	3		2
	wordCat * TypeOfStudy * Gex	6		3
	wordCat * TypeOfStudy * NCS	6		3
	wordCat * TypeOfStudy * NCCR	6		3
Random Effects	Intercept[b]	1	Variance Components	1
	Intercept[b]	1	Variance Components	1
	Intercept[b]	1	Variance Components	1
Residual				1
Total		51		32

Model Dimension[a]

		Subject Variables
Fixed Effects	Intercept	
	Gender	
	wordCat	
	TypeOfStudy	
	Gex	
	NCS	
	NCCR	
	score	
	wordCat * TypeOfStudy	
	wordCat * Gex	
	wordCat * NCS	
	wordCat * NCCR	
	wordCat * score	

	wordCat * TypeOfStudy * Gex	
	wordCat * TypeOfStudy * NCS	
	wordCat * TypeOfStudy * NCCR	
Random Effects	Intercept[b]	participant
	Intercept[b]	targetWord
	Intercept[b]	prime
Residual		
Total		

a. Dependent Variable: RT.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]	
-2 Restricted Log Likelihood	-928,597
Akaike's Information Criterion (AIC)	-920,597
Hurvich and Tsai's Criterion (AICC)	-920,583
Bozdogan's Criterion (CAIC)	-892,930
Schwarz's Bayesian Criterion (BIC)	-896,930

The information criteria are displayed in smaller-is-better forms.[a]

a. Dependent Variable: RT.

Fixed Effects

Type III Tests of Fixed Effects[a]				
Source	Numerator df	Denominator df	F	Sig.
Intercept	1	11,092	124,529	,000
Gender	1	9,954	3,830	,079
wordCat	2	1225,931	1,539	,215
TypeOfStudy	1	10,011	1,410	,262
Gex	1	10,007	,095	,764
NCS	1	10,000	,046	,835
NCCR	1	10,025	1,268	,286

score	1	81,935	,304	,583
wordCat * TypeOfStudy	2	2696,295	1,570	,208
wordCat * Gex	2	2700,102	,756	,470
wordCat * NCS	2	2696,740	,599	,549
wordCat * NCCR	2	2699,819	,196	,822
wordCat * score	2	2725,270	2,330	,098
wordCat * TypeOfStudy * Gex	3	25,856	,396	,757
wordCat * TypeOfStudy * NCS	3	25,861	1,391	,268
wordCat * TypeOfStudy * NCCR	3	25,840	1,008	,405

a. Dependent Variable: RT.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	,480424	,094084	10,983	5,106	,000	,273308
[Gender=1]	,179466	,091702	9,954	1,957	,079	-,024987
[Gender=2]	0[b]	0	.	.	.	.
[wordCat=human]	-,030959	,028501	1605,236	-1,086	,278	-,086863
[wordCat=neutral]	-,013822	,034866	1639,619	-,396	,692	-,082208
[wordCat=system]	0[b]	0	.	.	.	.
[TypeOfStudy=1,00]	,092763	,095546	10,657	,971	,353	-,118362
[TypeOfStudy=2,00]	0[b]	0	.	.	.	.
Gex	,031873	,036292	10,557	,878	,399	-,048417
NCS	-,023760	,063287	10,582	-,375	,715	-,163727
NCCR	,202152	,109400	10,295	1,848	,094	-,040661
score	,000765	,005204	265,237	,147	,883	-,009481
[wordCat=human] * [TypeOfStudy=1,00]	-,002954	,031521	2699,749	-,094	,925	-,064763
[wordCat=human] * [TypeOfStudy=2,00]	0[b]	0	.	.	.	.
[wordCat=neutral] * [TypeOfStudy=1,00]	,059795	,038046	2693,605	1,572	,116	-,014807
[wordCat=neutral] * [TypeOfStudy=2,00]	0[b]	0	.	.	.	.
[wordCat=system] *	0[b]	0	.	.	.	.

[TypeOfStudy=1,00]						
[wordCat=system] * [TypeOfStudy=2,00]	0[b]	0	.	.	.	.
[wordCat=human] * Gex	-,004770	,011268	2698,141	-,423	,672	-,026864
[wordCat=neutral] * Gex	,008130	,013633	2689,381	,596	,551	-,018601
[wordCat=system] * Gex	0[b]	0	.	.	.	.
[wordCat=human] * NCS	,019617	,020358	2698,165	,964	,335	-,020302
[wordCat=neutral] * NCS	,048360	,024697	2695,047	1,958	,050	-6,614374E-005
[wordCat=system] * NCS	0[b]	0	.	.	.	.
[wordCat=human] * NCCR	,039504	,026019	2694,904	1,518	,129	-,011515
[wordCat=neutral] * NCCR	,049641	,031156	2689,571	1,593	,111	-,011452
[wordCat=system] * NCCR	0[b]	0	.	.	.	.

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	,687539
[Gender=1]	,383919
[Gender=2]	.[b]
[wordCat=human]	,024945
[wordCat=neutral]	,054564
[wordCat=system]	.[b]
[TypeOfStudy=1,00]	,303889
[TypeOfStudy=2,00]	.[b]
Gex	,112162
NCS	,116206
NCCR	,444966
score	,011010
[wordCat=human] * [TypeOfStudy=1,00]	,058855
[wordCat=human] * [TypeOfStudy=2,00]	.[b]
[wordCat=neutral] * [TypeOfStudy=1,00]	,134398
[wordCat=neutral] * [TypeOfStudy=2,00]	.[b]
[wordCat=system] * [TypeOfStudy=1,00]	.[b]
[wordCat=system] * [TypeOfStudy=2,00]	.[b]
[wordCat=human] * Gex	,017324
[wordCat=neutral] * Gex	,034862
[wordCat=system] * Gex	.[b]
[wordCat=human] * NCS	,059535

[wordCat=neutral] * NCS	,096787
[wordCat=system] * NCS	.[b]
[wordCat=human] * NCCR	,090523
[wordCat=neutral] * NCCR	,110733
[wordCat=system] * NCCR	.[b]

Estimates of Fixed Effects[a]						
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
[wordCat=human] * score	,004040	,006479	2730,487	,623	,533	-,008665
[wordCat=neutral] * score	-,012762	,007907	2719,932	-1,614	,107	-,028266
[wordCat=system] * score	0[b]	0	.	.	.	.
[wordCat=human] * [TypeOfStudy=1,00] * Gex	-,032727	,199581	10,456	-,164	,873	-,474809
[wordCat=human] * [TypeOfStudy=2,00] * Gex	0	0	.	.	.	.
[wordCat=neutral] * [TypeOfStudy=1,00] * Gex	-,019126[b]	,203036	11,198	-,094	,927	-,465040
[wordCat=neutral] * [TypeOfStudy=2,00] * Gex	0	0	.	.	.	.
[wordCat=system] * [TypeOfStudy=1,00] * Gex	,026646[b]	,199642	10,468	,133	,896	-,415502
[wordCat=system] * [TypeOfStudy=2,00] * Gex	0	0	.	.	.	.
[wordCat=human] * [TypeOfStudy=1,00] * NCS	,000969	,093166	10,622	,010	,992	-,204982
[wordCat=human] * [TypeOfStudy=2,00] * NCS	0	0	.	.	.	.
[wordCat=neutral] * [TypeOfStudy=1,00] * NCS	-,062326	,095396	11,676	-,653	,526	-,270818
[wordCat=neutral] * [TypeOfStudy=2,00] * NCS	0	0	.	.	.	.
[wordCat=system] * [TypeOfStudy=1,00] * NCS	,008628[b]	,093096	10,590	,093	,928	-,197246
[wordCat=system] * [TypeOfStudy=2,00] * NCS	0	0	.	.	.	.
[wordCat=human] * [TypeOfStudy=1,00] * NCCR	-,223917[b]	,311455	10,444	-,719	,488	-,913907
[wordCat=human] * [TypeOfStudy=2,00] * NCCR	0[b]	0	.	.	.	.
[wordCat=neutral] * [TypeOfStudy=1,00] *	-,213220[b]	,316764	11,174	-,673	,515	-,909090

NCCR						

Estimates of Fixed Effects[a]	
Parameter	95% Confidence Interval
	Upper Bound
[wordCat=human] * score	,016744
[wordCat=neutral] * score	,002743
[wordCat=system] * score	.[b]
[wordCat=human] * [TypeOfStudy=1,00] * Gex	,409355
[wordCat=human] * [TypeOfStudy=2,00] * Gex	.
[wordCat=neutral] * [TypeOfStudy=1,00] * Gex	,426788[b]
[wordCat=neutral] * [TypeOfStudy=2,00] * Gex	.
[wordCat=system] * [TypeOfStudy=1,00] * Gex	,468793[b]
[wordCat=system] * [TypeOfStudy=2,00] * Gex	.
[wordCat=human] * [TypeOfStudy=1,00] * NCS	,206920
[wordCat=human] * [TypeOfStudy=2,00] * NCS	.
[wordCat=neutral] * [TypeOfStudy=1,00] * NCS	,146166
[wordCat=neutral] * [TypeOfStudy=2,00] * NCS	.
[wordCat=system] * [TypeOfStudy=1,00] * NCS	,214503[b]
[wordCat=system] * [TypeOfStudy=2,00] * NCS	.
[wordCat=human] * [TypeOfStudy=1,00] * NCCR	,466072[b]
[wordCat=human] * [TypeOfStudy=2,00] * NCCR	.[b]
[wordCat=neutral] * [TypeOfStudy=1,00] * NCCR	,482649[b]

Estimates of Fixed Effects[a]						
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
[wordCat=neutral] * [TypeOfStudy=2,00] * NCCR	0	0	.	.	.	.
[wordCat=system] * [TypeOfStudy=1,00] * NCCR	-,090539	,311486	10,448	-,291	,777	-,780561
[wordCat=system] * [TypeOfStudy=2,00] * NCCR	0[b]	0	.	.	.	.

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
[wordCat=neutral] * [TypeOfStudy=2,00] * NCCR	.
[wordCat=system] * [TypeOfStudy=1,00] * NCCR	,599483
[wordCat=system] * [TypeOfStudy=2,00] * NCCR	.[b]

a. Dependent Variable: RT.

b. This parameter is set to zero because it is redundant.

Covariance Parameters

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		,038688	,001058
Intercept [subject = participant]	Variance	,012058	,005525
Intercept [subject = targetWord]	Variance	,000115	,000159
Intercept [subject = prime]	Variance	,000266	,000188

a. Dependent Variable: RT.