BACHELOR THESIS

Differences in the perception of modern technological products.

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Abstract

People perceive products from all kinds of different viewpoints. It is important to note that some people have such special observational habits during the confrontation with an object, that it is worth the time to gain more knowledge about the properties that distinguish them from the other ones. This study has examined the perception of modern technological products and has laid its focus on gaining insights about people with a ‘Geek’-personality. The main aim was to find proof whether people exist who have this distinct ‘Geek’ way of perceiving things and whether people with this point of view are more common in a Psychology (PSY) or Computer-Science (CS) based study program. A Stroop task experiment with pictures of smartphones, laptops and tablets has been carried out to review if some participants need a longer reaction time for naming the color of a Geek labeled word. The acquired respond time for Geek words has been compared with the time needed for words that hold a Usability or Hedonistic meaning. Generally a higher reaction time indicates that the respondents where making certain associations with the shown products which were activated by the corresponding target words (Sparrow, Liu, & Wegner, 2011). The results have shown that we were not able to support the thesis that CS students consistently needed more time to respond to the Geek words than PSY students ($t = 0.235$, $p = 0.815$). Nevertheless a complex interaction effect was found that indicates that the mean reaction time for Hedonism- and Usability-terms for CS students had a much lower value compared to PSY students, whereas the mean reaction time for Geek-terms stayed almost the same. We expect future studies to be able to support this finding by using a greater sample size or a better statistical test with more power.

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1 Introduction

This thesis lays its focus on revealing differences between people concerning their approach to three important dimensions of a modern technological product. These dimensions include (1) ‘Identity/Social‘, (2) ‘Utility/Usability’ and (3) ’Understand/Master’. The hedonistic dimension (1) consists of attributes like whether or not the product has an appealing appearance or a good reputation in the perceivers’ social surroundings. People who have stronger associations with this dimension lay their focus on the possible pleasure a product might offer and are concerned about the image they obtain by buying a technological device. The usability dimension (2) in contrast focuses more on aspects such as the usefulness or practical applications of a product. People who respond relatively stronger to the Geek dimension (3) than to the first and second dimension can be expected to have a ‘Geek’ personality, in the way that they are motivated to gain broad knowledge about a product and to understand its inner processes.

1.1 Academic background

For the first two dimensions a number of researches have already been completed to frame relevant criteria for product quality. These gave rise to all different kinds of scales to measure the second dimension such as the ‘Usability Metric for User Experience’ (UMUX), which is a four-item Likert scale designed to assess the subjective perceived usability of an application (Finstad, 2010). It has been created to provide results comparable to those obtained with the 10-item ‘System Usability Scale’, which has been selected by the Information Technology department at Intel ® to standardize a usability inventory. The Usability Metric for User Experience is organized around the ‘ISO 9241-11’ definition of usability (1998). The results of the research have shown that the two scales correlate well, are reliable, and both align on one underlying usability factor. Additionally the Usability Metric for User Experience is compact enough to serve as a usability module in a broader user experience metric (Finstad, 2010).

Furthermore research concerning the first dimension has been conducted as well. An example for this is the work of Bargas-Avila and Hornbæk (2011) who have been reviewing the empirical research on ‘User Experience’ (UX). They state that non-instrumental, hedonic or non-task oriented goals are associated with ‘User Experience’, whereas instrumental, pragmatic or task-oriented goals are associated with usability. It has been found that the context of use and

anticipated use, which are often named key factors of 'User Experience', are rarely researched. These stand in contrast to emotions, enjoyment and aesthetics, which are by far the most frequently assessed aspects in 'User Experience' (Bargas-Avila & Hornbæk, 2011). On the other hand Hassenzahl, Burmester and Koller (2003) have been composing the "AttrakDiff 2" questionnaire to measure hedonic quality aspects of interactive products. These aspects are based on the human needs for stimulation and identity instead of the quality aspects of usability who were focused on the controlled manipulation of the environment. With this they have introduced a new method to assess quality aspects in a broader context (Hassenzahl, Burmester & Koller, 2003).

The interaction of these former dimensions with each other has been exposed to scientific interest as well. It was Hassenzahl and Monk (2010) for example who examined the relation between beauty and usability, with the implication: "what is beautiful is usable". They came to the conclusion that this complex interaction is mediated by goodness, using a mediator analysis of the relationship between beauty, the overall evaluation (goodness) and pragmatic quality (usability). It became clear that the supposed relationship between beauty and usability has been overrated and that goodness itself was completely accountable for the mediation between these two (Hassenzahl & Monk, 2010).

1.2 Geek Culture

Little research has been done though on the third composed dimension. This is a surprisingly fact because people with a Geek-personality and the Geek culture itself have an increasing impact to our society. There are lots of different examples who give an overview of the importance and popularity of this special subculture. One of them is the successful CBS comedy show "The Big Bang Theory" in which it is clear that the four main characters have a Geek-personality. The show displays the daily life of its characters and their problems interacting in common situations. The significance of the show can be found in its big fan base and number of viewers. In 2012 the fifth season was viewed by 15.8 million viewers and was even rated one of the top comedy shows (Mitovitch, 2012).

Other examples are associations such as "Anonymous" or the "Chaos Computer Club" which have an important influence on the society and political decision making as well. Members of these associations have a broad understanding of technological functions and are willing to engage in online as well as offline protests to draw attention to their goals. It is

reported that in 2012 “Anonymous” has been involved in paralyzing the British Home Office or in stealing 50 000 datasets from an job website which places IT-professionals in the financial sector (Horchert, 2012). This signals another aspect of the Geek culture which should not be forgotten.

Geeks were originally described as intelligent outcasts with an expertise in a certain topic and a lack of social skills (McArthur, 2009). It is important to note that the aim of this study is not to identify Geeks by means of a mental or social disorder such as autism or Asperger Syndrome, but to offer basic information as groundwork in which way their attitude towards technological products can be distinguished from the attitude of other persons. A hypothetical Geek is not a typical consumer in the way that they are generally well informed about today’s status and development of technological products (Rentel & Zellnik, 2007). They prefer to keep an updated knowledge and to give advice to non-informed people, which are willing to buy a new device, with the assistance of their broad insights.

1.3 Stroop Task and NFC

The experiment will be done by the assistance of the ‘Stroop task’ in a within subject design with massive repeated measures in contrast to questionnaires containing a Likert scale like they have been used by Finstad (2010). With this method are we trying gain insight in the unconscious processes involved in perceiving products instead of deliberately asking for the participants’ thoughts. This enables us to investigate a complete new aspect of this certain dimension.

The Stroop task contains in its original version a number of target words which are shown in different colors (Stroop, 1935). The challenge for the participants is to describe the color in which the words are written as fast as possible, although the meaning of the words hold a second independent color. The results indicated that it took the subjects more time to address the right color when the color of meaning and appearance differ from each other, compared to the condition where meaning and appearance hold the same type of color (Stroop, 1935).

Through the use of the Stroop task we are able to test the reaction times to the matched terms of the dimensions applied in this study after the appearance of a stimulus (a picture of a modern product such as smartphones, tablets or laptops). We expect that the subjects while seeing the stimuli are making particular associations with them, which are afterwords measured by evaluating the reaction time needed to respond to the targets colour. It has been proven that the targets meaning can have an interference effect with the assignation of its color (Kane &

Engle, 2003). People who have been disposed to think about a certain topic typically show slowed reaction times for naming the color of the word when the word itself is of interest and is more accessible, because the word captures attention (Sparrow, Liu, & Wegner, 2011). This means that if a persons sees a picture of a bank and makes an association with money, this person is likely to need more reaction time to appoint the color of an appearing word that has a close relation with "money" in contrast to an unrelated word.

This function is based on the 'Spreading Activation Theory' which holds that concepts are represented in memory as nodes and relations between them are represented as associative pathways (Balota & Lorch, 1986). When parts of the memory network are activated, actvision will spread along the associative pathways to connected areas in memory. This spread of activition serves to make these related parts of the memory network more available for further cognitive processing. Another fenomenon which is involved in the proces is 'Priming'. Priming is an unconscious form of cognitive memory which is independent from explicit memory (Tulving & Schacter, 1990). This means that features of stimuli are activating concepts in memory without the person beeing aware of it.

Furthermore the 'Need for Cognition' scale is going to be applied. This scale will be used to gather information about the cognitive properties of the participants (Cacioppo, Petty, & Kao, 1984). It has been stated that it describes:"…the tendency for an individual to engage in and enjoy cognitive thinking" (Cacioppo & Petty, 1982). The Need for Cognition scale has been proven to be effective in assassing these processes and offering structured results for comparison between the subjects.

1.4 Hypotheses

The first hypothesis questions if the proposed dimensions can be confirmed and if there exist significant differences between the 'Geek-Terms' (terms that hold a meaning of understanding as described in the third dimension) than 'Hedonism-Terms' (first dimension) or 'Usability-Terms' (second dimension).

The second hypothesis tries to find if persons in a Computer-Science based degree program respond stronger to the 'Geek-Terms' than persons in a Psychology degree program. Positive results could show that persons with a Geek-personality are more common in a computer-science program and support the compilation of the Geek-dimension.

The third hypothesis investigates whether persons with a high reaction time on 'Geek-Terms' score consistently higher on the 'Need for Cognition' scale. Supporting outcomes would confirm the classification of 'Geeks' and would indicate a relation between their perception and cognitive thinking.

2 Method

2.1 Sample

Dutch students of the 'University of Twente' participated in this study. To receive reliable results a total of 41 students took part and completed the Stroop task and the scale. From these 41 students, 16 were enrolled in a Computer-Science program and 25 were enrolled in a Psychology program. The participation for Computer-Science students was advertized by awarding six Euros for each subject and the chance to win one of two coupons with a value of 30 Euros. The participants from the Psychology program were assembled by giving out points at the university's research-subject system. Each student who is starting with the Psychology program has to achieve a certain amount of points in this system in the first two years.

2.2 Materials

The study took place in special research facility chambers to keep the chance of irritation through outside stimuli at a minimum. At the start of the experiment the participants were asked to start with the Stroop task. The subjects were briefed to use the Z, X, N and M keys to respond to the color of the shown targets (red, blue, green and yellow). Research has shown that with this attribution, the coordination between color and finger-usage stays as easy as possible (Besner, Stolz, & Boutilier, 1997). Furthermore they were instructed to stay focused and to direct their attention at the stimuli and the targets, which appeared after a short fixation of one second. They were confronted with a total of eight blocks each including 15 stimuli and targets. The 90 target words used in the main experiment were generated and then arranged by two evaluators into one of the three dimensions. Analysis has shown that Cohen's Kappa for these two evaluations had a value of 0.835 with a standard error of 0.049 and a statistical significance of $p < 0.000$. This level of agreement gives support for an acceptable inter-rater reliability.

Additionally it is important to mention that the subjects received a feedback after each target whether they made the right choice or not. This method further supported a high level of

concentration and prevented that the subjects respond in a random manner just to achieve low reaction times. The Stroop task experiment was designed by a program called 'E-prime' to create a user-friendly interface (Richard & Charbonneau, 2009). After completion of this part the Need for Cognition scale was assessed.

2.3 Procedure

At the beginning of the Stroop task, the subjects were starting with two training blocks to achieve a certain level of familiarity with the combination of color and the corresponding key. The stimuli offered in the training blocks were black-and-white pictures of 15 different fruits compared to the black-and-white pictures of 15 modern technological products that were used in the other blocks. These stimuli were shown for the duration of 5 seconds so that the participants had enough time to think about the product and memorize its features (MacLeod, 1991). To apply neutral targets we chose to use a line of five X ('XXXXX'). Through this method subjects were primed to focus on the color of appearance and to respond as fast as possible (Chen, Bailey, Tiernan, & West, 2011).

Starting with the third block, the participants were confronted with the main experiment. In this part of the experiment black-and-white pictures of five smartphones, five tablets and five laptops were randomized and of usage in each block. Because these products are quite popular, the brand marks were erased to exclude a possible bias. Following these stimuli, the terms of the three described domains (n=90) appeared in a random sequence over the next six blocks and the participants had to delineate whether they were shown in red, blue, yellow or green. From these 90 targets, 32 belonged to the first dimension (Hedonism-Terms), 28 to the second dimension (Usability-Terms) and 30 to the third dimension (Geek-Terms).The targets were classified into these dimension by two independent sources. To achieve the best results it was further chosen to display the targets in Dutch. By letting the students complete the task in their native language we created the best setting to observe the outcomes of the unconscious effects of the target specification on the reaction time. Examples for targets include words such as 'attractief' or 'populair' for Hedonism-terms, 'aanwenden' or 'veelzijdig' for Usability-terms and 'begrijpen' or 'systeem' for Geek-terms.

After the participants completed the Stroop task, they were confronted with the original 'Need for Cognition' scale composed by Cacioppo, Petty and Kao in 1984. This scale includes 18 different statements such as: "The notion of thinking abstractly is appealing to me". The

participants are asked to indicate whether or not the statement is characteristic for them by assigning a number running from 1 to 5. In this range “1” stands for “extremely uncharacteristic for me” and “5” for “extremely characteristic for me”.

When this part was finished as well, the subjects were debrieved and thanked for their participation.

2.4 Analysis

After the complete data-file had been collected, the proposed hypotheses were tested with the assistance of the statistics program ‘SPSS’. As part of the first Hypothesis an ‘Explorative Factor Analysis’ was assassed to validate the three dimensions. For the second hypothesis a number of ‘Independent-sample T-Tests’were conducted to review the interactions between the program of study and the mean score of reaction time for the three dimensions. Furthermore to compare the reaction time needed for ‘Geek-Terms’ with the results of the ‘Need for Cognition’ scale, the Pearson product-moment correlation coefficient was used. With this analysis we were able to make a clear appraisal whether these two results have some sort of correlation or not.

3 Results

It was the main ambition of this study to reveal basic differences in the perception of modern technological products between people and to find support for the three arranged dimensions. Furthermore we wanted to investigate whether Computer-Science students have a consistently higher reaction time on “Geek” valued terms than Psychology students. To confirm possible results we wanted to take a look at the relation between the reaction time on the Geek-terms and the results of the Need for Cognition Scale to see if a positive correlation exists.

Overall the mean reaction time needed to respond to the targets was 1006.91 ms with a standard deviation of 127,018. Furthermore the statistics for the implemented scales Hedonism (M = 1006.85, SD = 131.43) Usability (M = 980.39, SD = 125.39), Geek (M = 1031.72, SD = 157.38) and NFC (M = 3.69, SD = 0.55) have been analyzed as well.

3.1 Reliability

To make a deliberate evaluation of the internal consistency reliability associated with scores derived from each scale we first needed to recalculate the reaction time data by subtracting the mean reaction time from each subject. With this new achieved data it has been shown that the Cronbach’s Alpha coefficient for Usability-terms had a value of -0,369, for Hedonism-terms a

value of -0,265 and for Geek-terms a value of 0,020 (table 1). These indicators of a low level of reliability stand in contrast to the internal consistency reliability of the Need for Cognition Scale, which had a value of 0,877.

Table 1: *Internal Consistency Reliability*

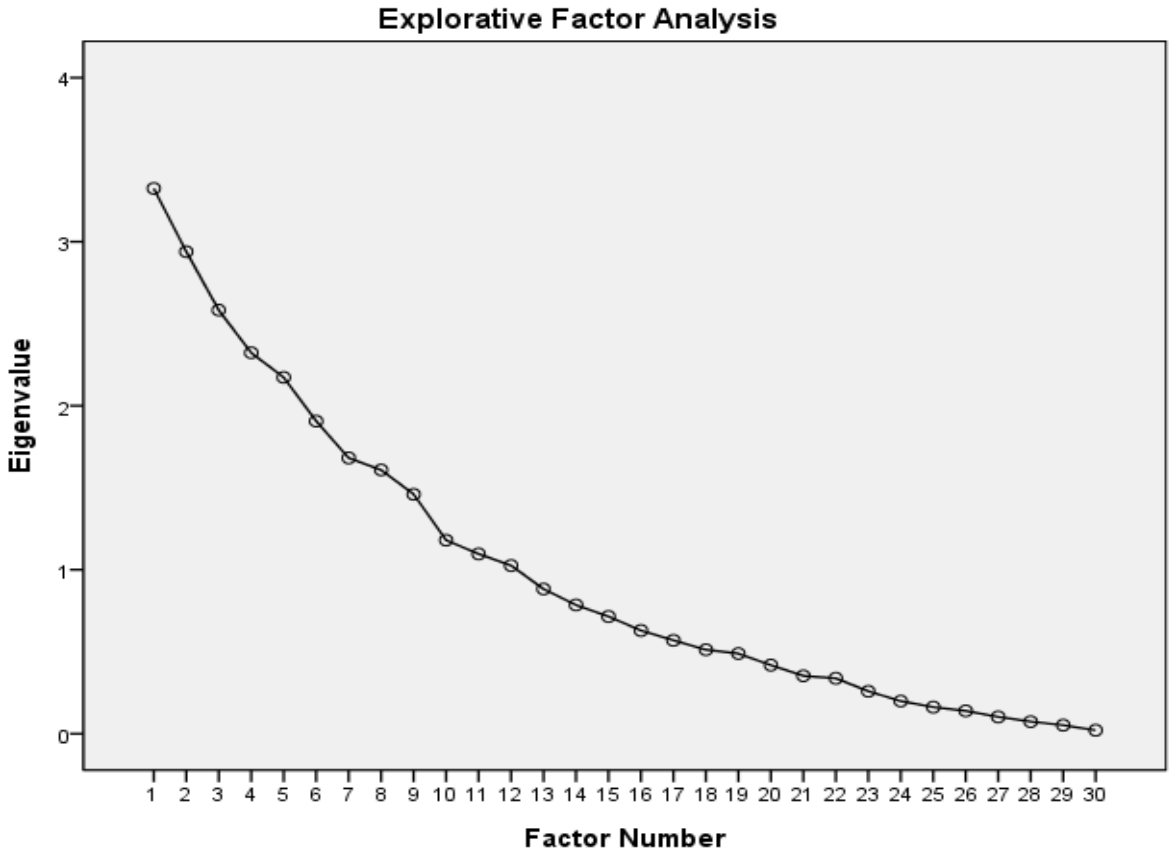
Scale	**Hedonism**	**Usability**	**Geek**	**NFC**
Number of items	32	28	30	18
Cronbach's alpha	-0.265	-0.369	0.020	0.877

3.2 Hypotheses

3.2.1 Confirmation of dimensions

For gaining insight in the first hypothesis (the confirmation of the three dimensions), an elaborative factor analysis has been conducted to inspect if the three dimensions can be found as underlying factors between items. To achieve a good calculation we have used the recalculated reaction time data (subtracted mean reaction time) and selected 10 representative items from each dimension and matched them to each other. This has happened in order to improve the item-respondent ratio to 1.36:1, which is necessary to carry out an explorative factor analysis. According to figure 1 it is obvious to see with the elbow criterion that two major bends were found after factor 4 and factor 7. These factors have a considerably higher eigenvalue than the other factors. This indicates that we are not able to certainly acknowledge the three dimensions as the only underlying factors.

Figure 1: *Explorative Factor Analysis*



3.2.2 Interaction between program and dimension

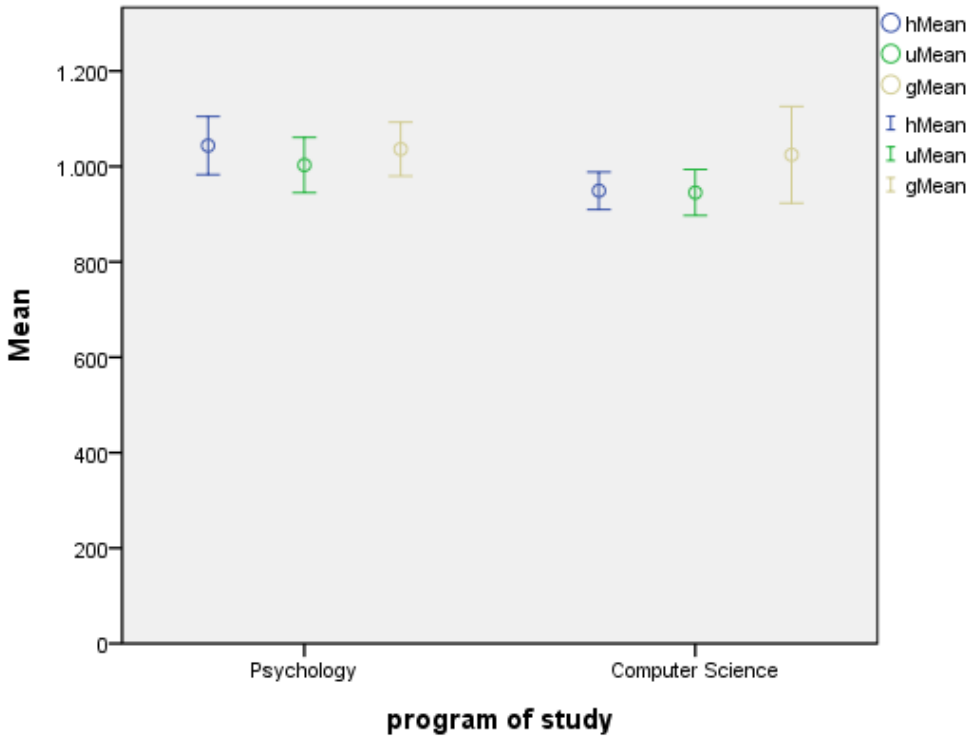
For the second hypothesis a number of 'Independent-Sample T-Tests' have been calculated to display the interaction of the different programs of study and the mean reaction time on each scale. It was found that on all scales, Psychology students had a larger reaction time than Computer-Science students, as seen in table 2.

Table 2: *Interaction Program-Dimension*

	PSY		**CS**	
Scale	**Mean**	**SD**	**Mean**	**SD**
Hedonism	1043.81	147.41	949.09	73.90
Usability	1002.87	140.44	945.26	90.636
Geek	1036.40	136.46	1024.41	190.17

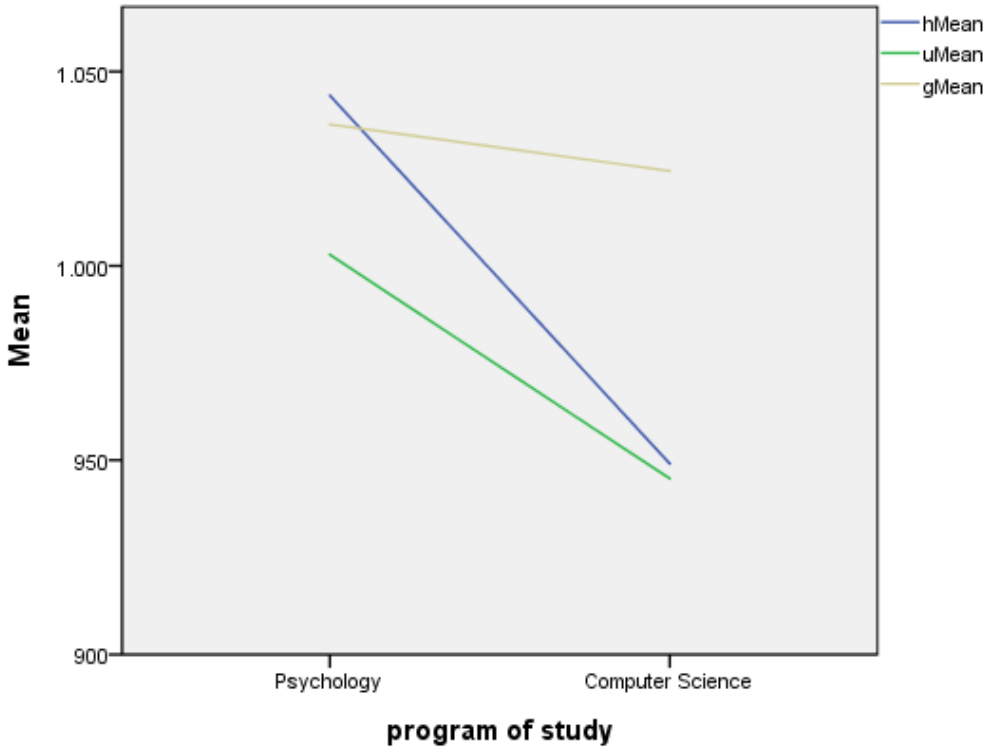
For giving a better overview, the results were summarized in figure 2.

Figure 2: *Overview Program of study-Scale Mean*



The test has shown that the enrolled program has a significant interaction with the Hedonism scale ($t = 2.379$, $p = 0.022$), a somewhat interaction with the Usability scale ($t = 1.455$, $p = 0.154$) and no significant interaction with the Geek scale ($t = 0.235$, $p = 0.815$). Although we could not provide evidence for a significant direct interaction between course and Geek scale, there is still proof for a complex interaction effect. In figure 3 it is clearly visible that the mean reaction time for Hedonism- and Usability-terms at computer science has a much lower value, whereas the mean reaction time for Geek-terms stays almost the same.

Figure 3: *Interaction Program of Study-Scale Mean*



3.2.3 Correlation Geek dimension and NFC

The third hypothesis questioned whether there exist a possible correlation between the mean reaction time for Geek-terms and the obtained score on the Need for Cognition scale. This thesis was tested by the 'Pearsons Correlation' coefficient. The outcomes delineate no significant correlations ($r = 0.117$, $p = 0.466$). The interaction between program of study and NFC score has quite an effect though. Analysis has shown that Computer-Science students ($M = 3.983$, $SD = 0.418$) score higher on the Need for Cognition scale than Psychology students ($M = 3.498$, $SD = 0.543$). Through the use of another independent sample T-Test this interaction effect was proven to be significant ($T = 3.037$, $p = 0.004$).

3.3 Learning effect

Additionally to review whether a learning effect can be found, we calculated the means of block 3 and block 8 (the beginning and end of the main part of the Stroop task). The results show that overall participants needed more time to respond at the beginning of the Stroop task ($M = 1067.69$, $SD = 219.55$) than at the end of the task ($M = 958.85$, $SD = 111.39$).

4 Discussion

It was the main aim of this study to reveal differences in the perception of modern products between people and to gain insight in the involved processes. Necessarily the validation of the three composed scales of Hedonism-, Usability- and Geek-terms has to be confirmed. For this purpose it is unsatisfying to see that the results of the Explorative Factor Analysis do not give sufficient evidence to draw such a conclusion.

The Explorative Factor Analysis is regarded as a powerful tool and generally preferred over the 'Principle Component Analysis' to reveal any latent variables that cause the manifest variables to covary (Costello & Osborne, 2005). During the analysis we avoided to retain all factors with an eigenvalue greater than 1.0 because this method is considered to be inaccurate for selecting the right number of factors to retain (Velicer & Jackson, 1990). A possible argument which could explain though why we received those unexpected results is the subject to item ratio. Although we had selected a total of 30 matched items out of the pool of 90 items, we still only obtained a subject to item of 1.36:1. In the existing literature it is stated that a ratio of 10:1 or less a still prevalent rule-of-thumb for determining the needed sample size (Costello & Osborne, 2005). It is obvious that our ratio is very low compared to this rule-of-thumb and might explain the found high number of underlying factors. Furthermore it is important to note that the Explorative Factor Analysis was originally designed for exploring a data set and not to test hypotheses or theories.

For evaluating the found data concerning the internal consistency reliability it needs to be mentioned that Cronbach's alpha is arguably the most commonly used metric for evaluating the internal consistency reliability associated with scores derived from a scale. Most researchers agree that Cronbach's alpha must be at least 0.70 to draw a valid conclusion (Nunnaly & Bernstein, 1994). It was pointed out by Lance, Butts and Michels (2006) that this often cited criterion is actually misleading. Essentially, Nunnaly and Bernstein (1994) state that 0.70 may be an acceptable minimum for a scale that is newly developed. However the found results for internal consistency reliability for the three dimensions clearly indicate a low level of reliability in contrast to the result for the Need for Cognition scale which indicates a confident high level of reliability. Although Cronbach's alpha identifies the lowest boundary of internal consistency reliability, it is evident that the reliability of the three dimensions is still very low or not existent. For explaining these findings it can be stated that the received signal might be too weak and that

the sample size could not be sufficient enough. A possible error during data- or item-coding is also a common mistake and could account for the low values of Cronbach's alpha (Nichols, 1999).

The Independent-Sample T-Tests executed in order to test the second hypothesis could not prove a significant interaction effect between the program of study and the mean reaction time obtained on the Geek dimension. The results even indicated that Computer Science students had a slightly lower mean reaction time than Psychology students. This finding stands in contrast to the proposed second hypothesis, which tried to find a higher reaction time for Computer Science students because of anticipated stronger associations with Geek-terms. It could be possible that Computer Science students have a generally higher familiarity with words that hold a meaning related to the Geek dimension. This would imply that not priming as a result of the shown pictures of modern technological products, but familiarity with the words has the major effect on responding to the targets.

Nevertheless while reviewing the T-Tests a quite interesting interaction effect came to the surface. As the results have shown in figure 3, Computer Science students clearly have a different distribution in the ranking of the three dimensions. Whereas Computer Science students have on average a lower reaction time on all scales than Psychology students, it is most certainly observable that their mean score on Geek-terms is averagely 75.32 milliseconds higher than the score on Hedonism-terms and 79.15 milliseconds higher than the Usability-terms. This emphasizes a trend that Computer Science students are more concerned with the Geek-features of a modern product than with its Hedonistic- or Usability-features. To give an example, they might focus their primary attention on aspects such as understanding the operation system instead on the appearance or the functional tools of the product. Psychology students in contrast seem to lay more emphasis on the Hedonistic-features as it can be seen in the results that their scored reaction time for Hedonism-terms is on average 7.41 milliseconds higher than their mean reaction time for Geek-terms and 40.94 ms higher than their reaction time for Usability-terms.

Last but not least it is important to mention that the found interaction effect between program of study and the score on the Need for Cognition scale is of importance as well. This effect indicates that Computer Science students are more likely to engage in and enjoy cognitive thinking. With a finding like this we can validate the found preference of CS students for Geek-terms, based on fact that both scales suggest a Geek-personality.

Although we were not able to offer significant proof for this particular conclusion, this effect still is of high interest and has a high research potential. We are confident that following studies will be able to support this finding by using a greater sample size or a better statistical test with more power. Follow-up studies might even come to think of assessing other scales which have been used in the field of Human-Computer interaction like the different models of Usability researched by Roy, Dewit and Aubert (2001). If the findings of this pilot study can be replicated and strengthened by a more deliberated study, we were able to make a first step in providing essential information about specific distinctions in the perception of product features. A somewhat different approach would focus on using a qualitative data assessment. An example for this would be a simple interview or open questionnaire. With this method people would be able to report their thought processes directly while perceiving products and might offer further insights.

The findings concerning Geekism found in this study are of great importance for the fields of Human-Computer interaction and product development. For HCI the hypothetical Geekism means for example that user interfaces have to take into account that some of their customers already have a broad understanding of the ongoing functions in the computer and are rather interested in the specific relations between these components. It is necessary for HCI to establish ways which make it possible to look up these relations in an easy manner. On the other hand the field of product development needs to keep an eye on creating access points for users to model a product themselves. This action would satisfy a great part of consumers who feel the need to adjust a product for their own personal usage.

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6 Appendix

6.1 SPSS Log Output

```
RELIABILITY
  /VARIABLES=t3a_u t3b_u t3f_u t3j_u t3l_u t3m_u t4b_u t4d_u t4h_u t4j_u
t4m_u t5c_u t5i_u t6b_u t6c_u t6d_u t6g_u t7a_u t6o_u t7b_u t7c_u t7d_u t7k_u
t7n_u t8c_u t8h_u t8m_u t8n_u
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=t3c_h t3k_h t3n_h t3o_h t4c_h t4e_h t4g_h t4k_h t4o_h t5a_h
t5b_h t5d_h t5e_h t5g_h t5h_h t5m_h t5n_h t5o_h t6f_h t6i_h t6j_h t6k_h t6m_h
t7f_h t7e_h t7h_h t7j_h t7l_h t8b_h t8a_h t8f_h t8o_h
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=t3d_g t3e_g t3g_g t3h_g t3i_g t4a_g t4f_g t4i_g t4l_g t4n_g
t5f_g t5j_g t5k_g t5l_g t6a_g t6h_g t6e_g t6l_g t6n_g t7g_g t7i_g t7m_g t7o_g
t8d_g t8e_g t8g_g t8i_g t8j_g t8k_g t8l_g
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RECODE q3 q4 q5 q7 q8 q9 q12 q16 q17 (1=5) (2=4) (3=3) (4=2) (5=1).
EXECUTE.
COMPUTE qMean=(q1 + q2 + q3 + q4 + q5 + q6 + q7 + q8 + q9 + q10 + q11 + q12 +
q13 + q14 + q15 + q16 + q17 + q18) / 18.
EXECUTE.
SAVE OUTFILE='H:\Bachelor\analyse\Bachelor SPSS.sav' /COMPRESSED.
SAVE OUTFILE='H:\Bachelor\analyse\Bachelor SPSS.sav' /COMPRESSED.
SAVE OUTFILE='H:\Bachelor\analyse\Bachelor SPSS version 2.sav'
  /COMPRESSED.
SAVE OUTFILE='H:\Bachelor\analyse\Bachelor SPSS version 2.sav' /COMPRESSED.
COMPUTE reactiontimeMean=(t3a_u + t3b_u + t3c_h + t3d_g + t3e_g + t3f_u +
t3g_g + t3h_g + t3i_g + t3j_u + t3k_h + t3l_u + t3m_u + t3n_h + t3o_h + t4a_g
+ t4b_u + t4c_h + t4d_u + t4e_h + t4f_g + t4g_h + t4h_u + t4i_g + t4j_u +
t4k_h + t4l_g + t4m_u + t4n_g
+ t4o_h + t5a_h + t5b_h + t5c_u + t5d_h + t5e_h + t5f_g + t5g_h + t5h_h +
t5i_u + t5j_g + t5k_g + t5l_g + t5m_h + t5n_h + t5o_h + t6a_g + t6b_u + t6c_u
+ t6d_u + t6e_g + t6f_h + t6g_u + t6h_g + t6i_h + t6j_h + t6k_h + t6l_g +
t6m_h + t6n_g + t6o_u + t7a_u
+ t7b_u + t7c_u + t7d_u + t7e_h + t7f_h + t7g_g + t7h_h + t7i_g + t7j_h +
t7k_u + t7l_h + t7m_g + t7n_u + t7o_g + t8a_h + t8b_h + t8c_u + t8d_g + t8e_g
+ t8f_h + t8g_g + t8h_u + t8i_g + t8j_g + t8k_g + t8l_g + t8m_u + t8n_u +
t8o_h) / 90.
EXECUTE.
COMPUTE r3a_u=t3a_u - reactiontimeMean.
EXECUTE.
COMPUTE r3b_u=t3b_u - reactiontimeMean.
EXECUTE.
COMPUTE r3c_h=t3c_h - reactiontimeMean.
EXECUTE.
```

```
COMPUTE r3d_g=t3d_g- reactiontimeMean.
EXECUTE.
COMPUTE r3e_g=t3e_g- reactiontimeMean.
EXECUTE.
COMPUTE r3f_u=t3f_u- reactiontimeMean.
EXECUTE.
COMPUTE r3g_g=t3g_g- reactiontimeMean.
EXECUTE.
COMPUTE r3h_g=t3h_g- reactiontimeMean.
EXECUTE.
COMPUTE r3i_g=t3i_g- reactiontimeMean.
EXECUTE.
COMPUTE r3j_u=t3j_u- reactiontimeMean.
EXECUTE.
COMPUTE r3k_h=t3k_h- reactiontimeMean.
EXECUTE.
COMPUTE r3l_u=t3l_u- reactiontimeMean.
EXECUTE.
COMPUTE r3m_u=t3m_u- reactiontimeMean.
EXECUTE.
COMPUTE r3n_h=t3n_h- reactiontimeMean.
EXECUTE.
COMPUTE r3o_h=t3o_h- reactiontimeMean.
EXECUTE.
COMPUTE r4a_g=t4a_g- reactiontimeMean.
EXECUTE.
COMPUTE r4b_u=t4b_u- reactiontimeMean.
EXECUTE.
COMPUTE r4c_h=t4c_h- reactiontimeMean.
EXECUTE.
COMPUTE r4d_u=t4d_u- reactiontimeMean.
EXECUTE.
COMPUTE r4e_h=t4e_h- reactiontimeMean.
EXECUTE.
COMPUTE r4f_g=t4f_g- reactiontimeMean.
EXECUTE.
COMPUTE r4g_h=t4g_h- reactiontimeMean.
EXECUTE.
COMPUTE r4h_u=t4h_u- reactiontimeMean.
EXECUTE.
COMPUTE r4i_g=t4i_g- reactiontimeMean.
EXECUTE.
COMPUTE r4j_u=t4j_u- reactiontimeMean.
EXECUTE.
COMPUTE r4k_h=t4k_h- reactiontimeMean.
EXECUTE.
COMPUTE r4l_g=t4l_g- reactiontimeMean.
EXECUTE.
COMPUTE r4m_u=t4m_u- reactiontimeMean.
EXECUTE.
COMPUTE r4n_g=t4n_g- reactiontimeMean.
EXECUTE.
COMPUTE r4o_h=t4o_h- reactiontimeMean.
EXECUTE.
COMPUTE r5a_h=t5a_h- reactiontimeMean.
EXECUTE.
COMPUTE r5b_h=t5b_h- reactiontimeMean.
```

```
EXECUTE.
COMPUTE r5c_u=t5c_u- reactiontimeMean.
EXECUTE.
COMPUTE r5d_h=t5d_h- reactiontimeMean.
EXECUTE.
COMPUTE r5e_h=t5e_h- reactiontimeMean.
EXECUTE.
COMPUTE r5f_g=t5f_g- reactiontimeMean.
EXECUTE.
COMPUTE r5g_h=t5g_h- reactiontimeMean.
EXECUTE.
COMPUTE r5h_h=t5h_h- reactiontimeMean.
EXECUTE.
COMPUTE r5i_u=t5i_u- reactiontimeMean.
EXECUTE.
COMPUTE r5j_g=t5j_g- reactiontimeMean.
EXECUTE.
COMPUTE r5k_g=t5k_g- reactiontimeMean.
EXECUTE.
COMPUTE r5l_g=t5l_g- reactiontimeMean.
EXECUTE.
COMPUTE r5m_h=t5m_h- reactiontimeMean.
EXECUTE.
COMPUTE r5n_h=t5n_h- reactiontimeMean.
EXECUTE.
COMPUTE r5o_h=t5o_h- reactiontimeMean.
EXECUTE.
COMPUTE r6a_g=t6a_g- reactiontimeMean.
EXECUTE.
COMPUTE r6b_u=t6b_u- reactiontimeMean.
EXECUTE.
COMPUTE r6c_u=t6c_u- reactiontimeMean.
EXECUTE.
COMPUTE r6d_u=t6d_u- reactiontimeMean.
EXECUTE.
COMPUTE r6e_g=t6e_g- reactiontimeMean.
EXECUTE.
COMPUTE r6f_h=t6f_h- reactiontimeMean.
EXECUTE.
COMPUTE r6g_u=t6g_u- reactiontimeMean.
EXECUTE.
COMPUTE r6h_g=t6h_g- reactiontimeMean.
EXECUTE.
COMPUTE r6i_h=t6i_h- reactiontimeMean.
EXECUTE.
COMPUTE r6j_h=t6j_h- reactiontimeMean.
EXECUTE.
COMPUTE r6k_h=t6k_h- reactiontimeMean.
EXECUTE.
COMPUTE r6l_g=t6l_g- reactiontimeMean.
EXECUTE.
COMPUTE r6m_h=t6m_h- reactiontimeMean.
EXECUTE.
COMPUTE r6n_g=t6n_g- reactiontimeMean.
EXECUTE.
COMPUTE r6o_u=t6o_u- reactiontimeMean.
EXECUTE.
```

```
COMPUTE r7a_u=t7a_u- reactiontimeMean.
EXECUTE.
COMPUTE r7b_u=t7b_u- reactiontimeMean.
EXECUTE.
COMPUTE r7c_u=t7c_u- reactiontimeMean.
EXECUTE.
COMPUTE r7d_u=t7d_u- reactiontimeMean.
EXECUTE.
COMPUTE r7e_h=t7e_h- reactiontimeMean.
EXECUTE.
COMPUTE r7f_h=t7f_h- reactiontimeMean.
EXECUTE.
COMPUTE r7g_g=t7g_g- reactiontimeMean.
EXECUTE.
COMPUTE r7h_h=t7h_h- reactiontimeMean.
EXECUTE.
COMPUTE r7i_g=t7i_g- reactiontimeMean.
EXECUTE.
COMPUTE r7j_h=t7j_h- reactiontimeMean.
EXECUTE.
COMPUTE r7k_u=t7k_u- reactiontimeMean.
EXECUTE.
COMPUTE r7l_h=t7l_h- reactiontimeMean.
EXECUTE.
COMPUTE r7m_g=t7m_g- reactiontimeMean.
EXECUTE.
COMPUTE r7n_u=t7n_u- reactiontimeMean.
EXECUTE.
COMPUTE r7o_g=t7o_g- reactiontimeMean.
EXECUTE.
COMPUTE r8a_h=t8a_h- reactiontimeMean.
EXECUTE.
COMPUTE r8b_h=t8b_h- reactiontimeMean.
EXECUTE.
COMPUTE r8c_u=t8c_u- reactiontimeMean.
EXECUTE.
COMPUTE r8d_g=t8d_g- reactiontimeMean.
EXECUTE.
COMPUTE r8e_g=t8e_g- reactiontimeMean.
EXECUTE.
COMPUTE r8f_h=t8f_h- reactiontimeMean.
EXECUTE.
COMPUTE r8g_g=t8g_g- reactiontimeMean.
EXECUTE.
COMPUTE r8h_u=t8h_u- reactiontimeMean.
EXECUTE.
COMPUTE r8i_g=t8i_g- reactiontimeMean.
EXECUTE.
COMPUTE r8j_g=t8j_g- reactiontimeMean.
EXECUTE.
COMPUTE r8k_g=t8k_g- reactiontimeMean.
EXECUTE.
COMPUTE r8l_g=t8l_g- reactiontimeMean.
EXECUTE.
COMPUTE r8m_u=t8m_u- reactiontimeMean.
EXECUTE.
COMPUTE r8n_u=t8n_u- reactiontimeMean.
```

```
EXECUTE.
COMPUTE r8o_h=t8o_h- reactiontimeMean.
EXECUTE.
RELIABILITY
  /VARIABLES=r3a_u r3b_u r3c_h r3d_g r3e_g r3f_u r3g_g r3h_g r3i_g r3j_u
r3k_h r3l_u r3m_u r3n_h r3o_h r4a_g r4b_u r4c_h r4d_u r4e_h r4f_g r4g_h r4h_u
r4i_g r4j_u r4k_h r4l_g r4m_u r4n_g r4o_h r5a_h r5b_h r5c_u r5d_h r5e_h r5f_g
r5g_h r5h_h r5i_u r5j_g
r5k_g r5l_g r5m_h r5n_h r5o_h r6a_g r6b_u r6c_u r6d_u r6e_g r6f_h r6g_u r6h_g
r6i_h r6j_h r6k_h r6l_g r6m_h r6n_g r6o_u r7a_u r7b_u r7c_u r7d_u r7e_h r7f_h
r7g_g r7h_h r7i_g r7j_h r7k_u r7l_h r7m_g r7n_u r7o_g r8a_h r8b_h r8c_u r8d_g
r8e_g r8f_h r8g_g
r8h_u r8i_g r8j_g r8k_g r8l_g r8m_u r8n_u r8o_h
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=r3a_u r3b_u r3f_u r3j_u r3l_u r3m_u r4b_u r4h_u r4j_u r4m_u
r5c_u r5i_u r6b_u r6c_u r6d_u r6g_u r6o_u r7a_u r7b_u r7c_u r7d_u r7k_u r7n_u
r8c_u r8h_u r8m_u r8n_u r4d_u
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=r3d_g r3e_g r3g_g r3h_g r3i_g r4a_g r4f_g r4i_g r4l_g r4n_g
r5f_g r5j_g r5k_g r5l_g r6a_g r6e_g r6h_g r6l_g r6n_g r7g_g r7i_g r7m_g r7o_g
r8d_g r8e_g r8g_g r8i_g r8j_g r8k_g r8l_g
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=r3c_h r3k_h r3n_h r3o_h r4c_h r4e_h r4g_h r6i_h r6j_h r6k_h
r4k_h r4o_h r5a_h r5b_h r5d_h r5e_h r5g_h r5h_h r5m_h r5n_h r5o_h r6f_h r6m_h
r7e_h r7f_h r7h_h r7j_h r7l_h r8a_h r8b_h r8f_h r8o_h
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
RELIABILITY
  /VARIABLES=q1 q2 q3 q4 q5 q6 q7 q8 q9 q10 q11 q12 q13 q14 q15 q16 q17 q18
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE CORR
  /SUMMARY=TOTAL.
SAVE OUTFILE='E:\Bachelor\analyse\Bachelor SPSS reactiontimeMean.sav'
 /COMPRESSED.
* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=studie MEANCI(hMean, 95.)
MEANCI(uMean, 95.) MEANCI(gMean, 95.) MISSING=LISTWISE REPOR
   TMISSING=NO
    TRANSFORM=VARSTOCASES(SUMMARY="#SUMMARY" INDEX="#INDEX" LOW="#LOW"
HIGH="#HIGH")
  /GRAPHSPEC SOURCE=INLINE.
```

```
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: studie=col(source(s), name("studie"), unit.category())
  DATA: SUMMARY=col(source(s), name("#SUMMARY"))
  DATA: INDEX=col(source(s), name("#INDEX"), unit.category())
  DATA: LOW=col(source(s), name("#LOW"))
  DATA: HIGH=col(source(s), name("#HIGH"))
  COORD: rect(dim(1,2), cluster(3,0))
  GUIDE: axis(dim(3), label("studie"))
  GUIDE: axis(dim(2), label("Mean"))
  GUIDE: legend(aesthetic(aesthetic.color.exterior), label(""))
  GUIDE: text.footnote(label("Error Bars: 95% CI"))
  SCALE: cat(dim(3), include("1", "2"))
  SCALE: linear(dim(2), include(0))
  SCALE: cat(aesthetic(aesthetic.color.exterior), include("0", "1", "2"))
  SCALE: cat(dim(1), include("0", "1", "2"))
  ELEMENT: point(position(INDEX*SUMMARY*studie), color.exterior(INDEX))
  ELEMENT: interval(position(region.spread.range(INDEX*(LOW+HIGH)*studie)),
shape.interior(shape.ibeam), color.interior(INDEX))
END GPL.

UNIANOVA gMean BY studie
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /EMMEANS=TABLES(studie) COMPARE ADJ(BONFERRONI)
  /PRINT=DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=studie.

UNIANOVA qMean BY studie
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /EMMEANS=TABLES(studie) COMPARE ADJ(BONFERRONI)
  /PRINT=DESCRIPTIVE
  /CRITERIA=ALPHA(.05)
  /DESIGN=studie.

DESCRIPTIVES VARIABLES=hMean uMean gMean qMean reactiontimeMean
  /STATISTICS=MEAN STDDEV MIN MAX.

FACTOR
  /VARIABLES r3a_uX r3d_gX r3f_uX r3i_gX r3k_hX r3m_uX r4a_gX r4c_hX r4e_hX
r4k_hX r4n_gX r4o_hX r5b_hX r5f_gX r5i_uX r5o_hX r6c_uX r6h_gX r6j_hX r6k_hX
r7b_uX r7c_uX r7g_gX r7h_hX r7i_gX r7n_uX r8g_gX r8h_uX r8k_gX r8n_uX
  /MISSING LISTWISE
  /ANALYSIS r3a_uX r3d_gX r3f_uX r3i_gX r3k_hX r3m_uX r4a_gX r4c_hX r4e_hX
r4k_hX r4n_gX r4o_hX r5b_hX r5f_gX r5i_uX r5o_hX r6c_uX r6h_gX r6j_hX r6k_hX
r7b_uX r7c_uX r7g_gX r7h_hX r7i_gX r7n_uX r8g_gX r8h_uX r8k_gX r8n_uX
  /PRINT INITIAL CORRELATION KMO ROTATION
  /FORMAT SORT BLANK(.10)
  /PLOT EIGEN
  /CRITERIA FACTORS(9) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
  /ROTATION VARIMAX
  /METHOD=CORRELATION.
```

```
T-TEST GROUPS=studie(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=hMean
  /CRITERIA=CI(.95).

T-TEST GROUPS=studie(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=uMean
  /CRITERIA=CI(.95).

T-TEST GROUPS=studie(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=gMean
  /CRITERIA=CI(.95).

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=studie MEANCI(hMean, 95.)
MEANCI(uMean, 95.) MEANCI(gMean, 95.) MISSING=LISTWISE REPORTMISSING=NO
    TRANSFORM=VARSTOCASES(SUMMARY="#SUMMARY" INDEX="#INDEX" LOW="#LOW"
HIGH="#HIGH")
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: studie=col(source(s), name("studie"), unit.category())
  DATA: SUMMARY=col(source(s), name("#SUMMARY"))
  DATA: INDEX=col(source(s), name("#INDEX"), unit.category())
  DATA: LOW=col(source(s), name("#LOW"))
  DATA: HIGH=col(source(s), name("#HIGH"))
  COORD: rect(dim(1,2), cluster(3,0))
  GUIDE: axis(dim(3), label("studie"))
  GUIDE: axis(dim(2), label("Mean"))
  GUIDE: legend(aesthetic(aesthetic.color.exterior), label(""))
  GUIDE: text.footnote(label("Error Bars: 95% CI"))
  SCALE: cat(dim(3), include("1", "2"))
  SCALE: linear(dim(2), include(0))
  SCALE: cat(aesthetic(aesthetic.color.exterior), include("0", "1", "2"))
  SCALE: cat(dim(1), include("0", "1", "2"))
  ELEMENT: point(position(INDEX*SUMMARY*studie), color.exterior(INDEX))
  ELEMENT: interval(position(region.spread.range(INDEX*(LOW+HIGH)*studie)),
shape.interior(shape.ibeam), color.interior(INDEX))
END GPL.

* Chart Builder.
GGRAPH
  /GRAPHDATASET NAME="graphdataset" VARIABLES=studie MEAN(hMean) MEAN(uMean)
MEAN(gMean) MISSING=LISTWISE REPORTMISSING=NO
    TRANSFORM=VARSTOCASES(SUMMARY="#SUMMARY" INDEX="#INDEX")
  /GRAPHSPEC SOURCE=INLINE.
BEGIN GPL
  SOURCE: s=userSource(id("graphdataset"))
  DATA: studie=col(source(s), name("studie"), unit.category())
  DATA: SUMMARY=col(source(s), name("#SUMMARY"))
  DATA: INDEX=col(source(s), name("#INDEX"), unit.category())
  GUIDE: axis(dim(1), label("studie"))
  GUIDE: axis(dim(2), label("Mean"))
  GUIDE: legend(aesthetic(aesthetic.color.interior), label(""))
```

```
  SCALE: cat(dim(1), include("1", "2"))
  SCALE: linear(dim(2), include(0))
  SCALE: cat(aesthetic(aesthetic.color.interior), include("0", "1", "2"))
  ELEMENT: line(position(studie*SUMMARY), color.interior(INDEX),
missing.wings())
END GPL.

CORRELATIONS
  /VARIABLES=qMean gMean
  /PRINT=TWOTAIL NOSIG
  /STATISTICS DESCRIPTIVES
  /MISSING=PAIRWISE.

T-TEST GROUPS=studie(1 2)
  /MISSING=ANALYSIS
  /VARIABLES=qMean
  /CRITERIA=CI(.95).

COMPUTE Block3Mean=(t3a_u + t3b_u + t3c_h + t3d_g + t3e_g + t3f_u + t3g_g +
t3h_g + t3i_g + t3j_u + t3k_h + t3l_u + t3m_u + t3n_h + t3o_h) / 15.
EXECUTE.
COMPUTE Block8Mean=(t8a_h + t8b_h + t8c_u + t8d_g + t8e_g + t8f_h + t8g_g +
t8h_u + t8i_g + t8j_g + t8k_g + t8l_g + t8m_u + t8n_u + t8o_h) / 15.
EXECUTE.
DESCRIPTIVES VARIABLES=Block3Mean Block8Mean
  /STATISTICS=MEAN STDDEV MIN MAX.
```

6.2 Need for Cognition scale

Need for Cognition Scale (from Cacioppo, Petty, & Kao, 1984)

For each of the statements below, please indicate whether or not the statement is characteristic of you or of what you believe. For example, if the statement is extremely uncharacteristic of you or of what you believe about yourself (not at all like you) please place a "1" on the line to the left of the statement. If the statement is extremely characteristic of you or of what you believe about yourself (very much like you) please place a "5" on the line to the left of the statement. You should use the following scale as you rate each of the statements below.

1	2	3	4	5
extremely uncharacteristic of me	somewhat uncharacteristic of me	uncertain	somewhat characteristic of me	extremely characteristic of me

1.___	I prefer complex to simple problems.
2.___	I like to have the responsibility of handling a situation that requires a lot of thinking.
3.___	Thinking is not my idea of fun.
4.___	I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.
5.___	I try to anticipate and avoid situations where there is a likely chance I will have to think in depth about something.
6.___	I find satisfaction in deliberating hard and for long hours.
7.___	I only think as hard as I have to.
8.___	I prefer to think about small daily projects to long term ones.
9.___	I like tasks that require little thought once I've learned them.
10.___	The idea of relying on thought to make my way to the top appeals to me.
11.___	I really enjoy a task that involves coming up with new solutions to problems.
12.___	Learning new ways to think doesn't excite me very much.
13.___	I prefer my life to be filled with puzzles I must solve.
14.___	The notion of thinking abstractly is appealing to me.
15.___	I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.
16.___	I feel relief rather than satisfaction after completing a task that requires a lot of mental effort.
17.___	It's enough for me that something gets the job done; I don't care how or why it works.

18.___	I usually end up deliberating about issues even when they do not affect me personally.