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The Relation Between Movie Clip Characteristics And The Evolution of Neural Reliability Over Time.

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Abstract

Neural activity is shown to accurately predict individual human behaviour. Recently, it has been shown that neural activity can be highly similar across audio-visually stimulated individuals, and the degree of this neural similarity across individuals can be linked to group behaviour. Neural reliability refers to this degree of similarity of neural activity between individuals and can be measured using an Inter-Subject Correlation (ISC) analysis. The degree of neural reliability can be measured through multiple brain activity measurements, such as an electroencephalogram (EEG) or functional magnetic resonance imaging (fMRI). Within this study the variation of neural activity over time is explored, therefore data with high temporal resolution are necessary. For this purpose, EEG data suit best. Besides the evolution over time of neural reliability, a crucial question is to understand how neural reliability is influenced by specific movie clip characteristics, since these characteristics might influence group behaviour. This study will assess which specific characteristics of the audio-visual stimuli are related to high levels of neural reliability. To this end, two movie clips are coded according to a tailor-made codebook and ISC and visual complexity measures are calculated. Multiple standard regression analyses are conducted to predict ISC from the specific characteristics and visual complexity measures. The results show that ISC can be predicted from mainly specific film technique characteristics and visual complexity measures. These findings may contribute to future research into this topic, concerning the specificity of audio-visual stimuli and its ability to evoke highly similar brain activity.

1 Introduction

Being high cognitive functioning creatures, humans value the uniqueness of each individual. The abilities we have to place more or less emphasis on this uniqueness, can be expressed by the choices made by every individual. To this end, many individual's choices are made on a daily basis. Some of the choices to express uniqueness are made consciously, for example the choice to dye one's hair pink to express exclusiveness (Heine, 2015). However, many daily choices are made in a split second, without hesitation and seemingly without influence from others. For example, daily one chooses to go to work or to study and not to stay at home and sleep all day. There are so many choices that can be made and the variety of options to choose from is enormous. Intuitively, this leads to the idea that there must be a vast variety in individual preferences. Why else would there be so much to choose? This variety of individual preferences, and the individual choices that come with it will express the uniqueness of each individual. At least, this is what we would like to think.

One of the choices that seems to be solely based on individual preference and therefore independent of influence from the environment, is the choice of watching a particular movie. Therefore, movies can be used to investigate whether choices are indeed solely based on individual preferences or whether choices are influenced by other stimuli, such as environmental influence. With this in mind, Boksem and Smidts (2015) tried to make a model in which individual preferences of commercially released movies could be predicted on the basis of neural measures, like EEG data. If preferences are indeed predictable, choices are influenced by other stimuli and thus would not be solely individual. To this end, the researchers collected EEG data and stated preference measures from participants who were viewing movie trailers of commercially released movies, under naturalistic viewing conditions. The stated preference measures were divided in rates for liking of the movie, willingness to pay for the DVD of the movie, and an ordered preference in which the participants had to sort the movies in descending order of preference. The results showed that a model with only willingness to pay was already highly predictive of individual preference. However, when adding EEG beta activity measures to this model, the model significantly improved. Thus, high beta activity during the viewing of a movie was related to a high preference for this movie. This means that the explained variance for predicting individual preferences significantly increased when adding the EEG data to the data for stated preference. Eventually, the researchers concluded that EEG measures, especially beta and gamma oscillations, provided unique information regarding individual preferences (Boksem, & Smidts, 2015). This research shows that individual preferences can be predicted on the basis of neural measurements. Therefore it can be concluded that choices are not solely individual and probably influenced by other stimuli. Boksem and Smidts (2015) investigated whether neural activity is related to preferences within subjects, thus the uniqueness of the neural measurement of each individual. However, neural activity may not only be similar within subjects, but also between subjects.

1.1 Neural reliability

To investigate whether neural activity is indeed similar between subjects, Dmochowski, Bezdek, Abelson, Johnson, Schumacher and Parra (2014) examined whether preferences of large audiences could be predicted from similarities in neural activity from a small sample of people. To this end, this small sample viewed several SuperBowl commercials while their neural activity was measured through EEG. Thereafter, similarity of the neural activity between all the individuals in the small sample was calculated. This similarity is referred to as neural reliability and is calculated by using an Inter-Subject Correlation (ISC) analysis. The use of an ISC analysis was introduced by Hasson, Landesman, Knappmeyer, Vallines, Rubin and Heeger (2008) in a fMRI study. These researchers developed the ISC analysis as a measure for neural reliability in the context of fMRI measurements. The analysis in their research showed that a high level of similarity, thus a high ISC, relates to similar activity across most viewers. Also, a low level of similarity, thus a low ISC, results in less similar brain activity (Hasson et al., 2008). Dmochowski et al. (2014) adapted the ISC analysis in order to use it in an EEG context. With this analysis the similarity between the response time course in electrodes from one viewer and the response time course in the same electrodes from other viewers could be observed (Dmochowski et al., 2014).

The results of Dmochowski et al. (2014) showed that the similarity of neural reliability in a small sample of people, who viewed a commercial, is highly predictive for the preference of the commercial. So, the extent to which individual brains react similarly while watching a commercial, will indicate how much a commercial is liked. Furthermore, the better a commercial is liked, the better the product will sell. Therefore, high neural reliability will predict more preference for the commercial, which will predict better sales and low neural reliability will predict less preference for the commercial, which will predict worse sales. Thus, neural reliability is highly predictive of across-stimuli preferences and also accurately predicts preferences of large audiences.

1.2 Stimuli characteristics

The study from Dmochowski et al. (2014) showed similarity in neural reliability over the whole commercial. However, neural reliability may vary over time and therefore some moments from a stimulus will elicit more neural reliability than other moments from the same stimulus. Subsequently, the question arises whether there are certain stimuli characteristics that are present at certain moments during the stimulus which can account for high neural reliability across individuals. A related question reads whether stimuli characteristics are predictive for high levels of neural reliability. Within this perspective, it is been shown that filmmakers try to control the viewer's attention and eye movements by using a variety of stylistic cinematic features, such as lighting and movement (Deldjoo, Elahi, Cremonesi, Garzotto, Piazzolla, & Quadrana, 2016). This directed attention results in a high ISC, whereas a low ISC is obtained when the filmmaker failed to direct the attention of the viewer. Low ISC could be interpreted as an increased individual interpretation of the undirected scene (Hasson et al., 2008). Low ISC can also be a result of the experience of positive emotions. Positive emotions can promote free exploration, which may result in our brains processing the sensory input more individually, and as a consequence, a low ISC. Negative emotions, on the other hand, can elicit more similar brain activity in the emotion circuit (Nummenmaa, Glerean, Viinikainen, Jääskeläinen, Hari, & Sams, 2012).

The previously mentioned studies showed that the neural activity elicited by audio-visual stimuli can accurately predict individual preferences and preferences of large audiences. Also, it has been shown that certain characteristics of a movie clip elicit certain brain activity that is shared across viewers. Continuing this line of research, it is interesting to investigate whether there are specific characteristics of audio-visual stimuli that can be linked to similarity in brain activity across subjects. Therefore, the question arises whether neural reliability and its evolution over time is related to and can be predicted from movie clip characteristics.

As described above, neural reliability is previously studied using fMRI and EEG data. Within this study, the evolution of neural reliability over time will be explored. For precisely measuring the variation in synchronization of brain activity over time, data that have a high temporal resolution are most suitable. Since EEG data have a higher temporal resolution than fMRI data, EEG data are used for this study. EEG measures the electrical activity which is produced by neurons in the brain. The electrical activity is generated rapidly within the brain and using EEG it is possible to capture these rapid changes in the electrical activity. On the other hand, fMRI data capture the BOLD response, which does not directly reflect the neural activity, but merely the blood-flow to the brain. This blood-flow is only a side effect of neural activity that occurs some seconds after when the neural activity took place. Moreover, the temporal relation between neural activity and the BOLD response has been shown to vary across brain regions, time and subjects. As such, fMRI has a low temporal resolution (Gazzaniga, Ivry, Mangun, 2014). However, the spatial resolution is for EEG data lower than for fMRI. Thus, for precisely measuring the location of synchronization in the brain, fMRI is more suitable. As the focus in this study is not on localising the brain activity that is responsible for the neural reliability, but rather on the stimuli characteristics that are related to neural reliability, which vary at short time scales (i.e., second to second), EEG is preferred over fMRI. Indeed, the high temporal resolution of EEG ensures that the (time-varying) synchronization of the different brains can be measured easily (Dmochowski, Sajda, Dias, & Parra, 2012; Dmochowski et al., 2014).

1.3 Research questions

In the current study the question will be answered whether neural reliability and its evolution over time is related to and can be predicted from specific movie clip characteristics. The question will be answered by conducting a standard regression analysis between ISC, calculated using the method from Dmochowski et al. (2014), based on the EEG data presented by Boksem and Smidts, (2015) and coded characteristics from the movie clips. The characteristics are coded through a codebook, specifically made for the movie clips.

In the remainder of this thesis, first the data will be presented and the coding scheme will be discussed (Section 2). Next, the results will be described (Section 3). Finally, a conclusion will be made and a discussion with limitations and suggestions for further research will be presented (Section 4).

2 Methods

2.1 Data

The EEG data used for this thesis are presented in Boksem and Smidts (2015).

Participants. Boksem and Smidts (2015) used thirty-two participants, recruited from the university population. One could not participate if he or she had experienced a neurological illness or damage, was using drugs or psychiatric medication and/or had abnormal vision. Because of EEG equipment failure, the data of one participant were not recorded, therefore this participant was excluded from the final sample. Besides this, two of the participants had excessive artefacts in their EEG recordings and therefore, they were also excluded. Thus, the final sample consisted of twenty-nine participants between 18 and 28 years (13 women), mean age of 21.5 years.

EEG procedure. When the participants arrived at the lab, they received detailed written and verbal instructions about the tasks they had to perform in the experiment. Next, 64 EEG electrodes were placed on the head of the participants and the participants were seated in a dimly lit, sound-attenuated, electrically shielded room at 1.80 meters from a 19-inch PC monitor. The participants viewed 18 movie trailers, from which two will be used for this study. Before the participants were to view the trailer, they were showed the DVD cover of the movie for 6 seconds, followed by a blank screen for 2.5 seconds. The movies included in the stimuli set of Boksem and Smidts (2015) did not include movies belonging to the top 150 most famous movies, to prevent the chance that participants would be familiar with the movie.

Movie clips. The movie clips which are used for this study are the trailers from the movies ‘Gracie’ and ‘Love and Basketball’. The duration of both trailers is approximately 2 minutes. They were viewed by the participants in a series of 18 trailers, for which the duration was approximately 50 minutes in total. The order in which the movie clips were shown is unknown. The choice for specifically these trailers is based on their similarities in content. Both movies are about sports, thus it can be expected that the EEG measures of participants who watched those movie clips will probably not differ on the basis of liking of the content (Gray & Bjorklund, 2014). Besides this, in both movies the main character is a girl, who is trying to show her environment that she is equally good, in comparison to boys, in the sport she practices. Furthermore, main themes in the scenes of both movies are training and winning or losing. The largest differences between both clips pertains to the ethnic background of the main characters. The characters from the movie ‘Gracie’ are Caucasian, whereas the characters are Afro-American in the movie ‘Love and Basketball’. This difference might show in the EEG measurements. Besides this, the movie ‘Love and Basketball’ incorporates a love story, whereas ‘Gracie’ is more about the perseverance of the main character. Lastly, ‘Gracie’ contains more outside scenes, whereas ‘Love and Basketball’ contains more indoor scenes, a difference which might also show in neural reliability measures.

2.2 Codebook

A codebook was constructed to indicate which specific movie clip characteristics occurred in every frame of the movie clip. The complete codebook can be found in Appendix A. To construct this codebook, the movie clips were examined and all that was seen in the movie clips was indicated. The codebook contains nine different categories, namely; Emotion, Film techniques, Sounds, Setting, Movement, Weather, Objects, Music and Interaction. The category Emotion can be coded whenever there is a reaction to an event or situation. Within this category, a distinction is made between positive and negative emotions, because information is processed differently when seeing a positive or negative emotion (Fox, 2008). Furthermore, four basic emotions, happiness, anger, fear and sadness, can be coded. The fifth and sixth basic emotions, surprise and disgust, are not taken into account, because it is too ambiguous to indicate when this emotions are shown. Within the category Film techniques, there were seven techniques observed within the two movie clips. These techniques may influence attention processes and encoding and storage of the content and can therefore be coded as such (Geiger & Reeves, 1993; Lang, Bolls, Poter, & Kawahara, 1999). Also, seven specific sounds were observed in the two movie clips, and are therefore included in the codebook. A specific sound may elicit brain activity. Next, the setting of each scene is included in the codebook, because different settings may influence how a scene is interpreted. Scenes inside a house are defined as unknown, because there are many different rooms inside a house and the distinctions between rooms are not always clearly framed. Besides this, indoor scenes are not given a day or night characteristic. Next, more than ten different movements can be coded in the category Movement, because movement from either the actor or the camera may influence neural activity (Reeves, Thorson, Rothschil, McDonald, Hirsch, & Goldstein, 1985). Movement of the camera is included in the category Film techniques. Movement of an actor or object can be coded when the main actor or object in the scene moved. Movement on the background of the scene is not coded. Weather is included as a specific category, since a sunny or rainy scene may induce a different mood and in this way elicit different brain activity. Furthermore, many different objects are included in the category Objects. This is because certain objects, like an alcoholic beverage, seem to have influence on how an actor is evaluated and this may influence brain activity (McIntosh, Smith, Bazzini, & Mills, 1999). The presence of music can also be coded, since musical cues seem to influence the involvement of viewers in the movie clip (Maccinnis, & Park, 1991). Lastly, interactions can be coded. Interaction through a verbal conversation is divided between a normal message, a question and shouting. These different forms of verbal conversation may elicit different brain activity. Non-verbal conversation is also included in the codebook.

2.3 Computations

Neural reliability. The computation for neural reliability is based on the method proposed by Dmochowski et al. (2014). A detailed description of the actual computation is presented in Appendix B. Measuring neural reliability can be done by using the Inter-Subject Correlation (ISC) analysis. This analysis quantifies the degree of similarity across multiple subjects of the neural activity when watching a stimulus (e.g., a trailer). The ISC in EEG is derived from a novel signal decomposition technique that ensures a maximal correlation by finding linear components in the data (Dmochowski et al., 2014). Thus, instead of using raw electrode-by electrode information, systematic patterns of activity distributed over large cortical areas are captured. The technique is similar to a canonical correlation analysis and is based on a maximum-likelihood formulation. However, when computing neural reliability, the same projection is used for all data sets. The purpose of the method is to project the data of all subjects onto a common space, such that the resulting projections exhibit maximal ISC across the subject pool (Dmochowski et al., 2014).

Visual complexity. Visual complexity can be assessed as the average statistical randomness of each frame of the movie clip. The movie clips contain approximately 24 frames per second. Each of these frames can be regarded as an image. To determine the visual complexity of these frames, the frames are converted from colour to greyscale. Thereafter, the entropy of each image can be computed. The visual complexity measures used for this study are the mean entropy and the variation in entropy. The mean entropy refers to the mean entropy of the 24 frames. Variation in entropy refers to the variance in entropy across the frames used for each time window. Images which are relatively uniform in intensity are regarded as low-entropy images, whereas high-entropy images have more contrasts. Because high-entropy images have many bright and dark areas, these images have also many focal points for visual attention which may influence neural reliability (Barnett, White, & Cerf, n.d.).

Coding. The actual coding was done using the programme ELAN 5.0.0-beta, which can be retrieved from https://tla.mpi.nl/tools/tla-tools/elan/. The codebook was uploaded in the programme. The nine main categories are labelled in the programme as ‘parent tiers’ and the other characteristics are labelled as ‘tiers’. For every characteristic ‘enter’ could be pressed to switch the characteristic on or off (Wittenburg, Brugman, Russel, Klassmann, & Sloetjes, 2006). This resulted in a coding scheme in which 1 represented the characteristic being present and 0 represented the characteristic being absent.

Sliding windows. A simple sliding window approach is used to assess the time variance. Within this approach, 1 second windows are taken and this window shifts every .5 seconds. So, the first window captures the time between the seconds 0 to 1, then the window shifts .5 seconds and the second window captures the time between the seconds .5 to 1.5. Thereafter the window shifts .5 seconds again and therefore, the third window captures the time between the seconds 1 to 2, etcetera. For every window, neural reliability measurements, entropy measurements and coding measurements are obtained. Concerning the coding measurements, a characteristic could be partly present in a window and therefore the coding scheme was not strictly divided in 1 and 0, but could also contain values between 1 and 0.

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2.4 Statistical Analyses

To evaluate whether specific movie clip characteristics can indeed predict neural reliability, multiple steps have to be taken. Firstly, the vast number of various characteristics are clustered into the main categories as represented in the codebook and for each category, a mean variable is computed. For example, the mean variable Emotion is the mean of the values for the specific characteristics Emotion, Positive, Happy, Negative, Sad, Anger, Unknown. This mean variable can contain any value between 0 and 1. This results in the computation of eight new mean variables (i.e., there are eight categories). The characteristic Music is interpreted as a main category variable, since this category does not include several specific characteristics. These main category variables are computed to explore which categories may predict ISC best, using a regression analysis.

Secondly, a regression analysis is done, using the eight mean variables, Music, Mean Entropy and Variation in Entropy as independent variables and ISC, computed through the method as presented by Dmochowski et al. (2014), as dependent variable. Mean Entropy and Variation in Entropy are included in this analysis, because these variables can be regarded as main categories which can influence ISC. To determine if a variable makes a statistically significant unique contribution to the prediction of ISC, a 5% significance level is assumed. To control for multicollinearity, all these variables are first included in a correlation analysis. Multicollinearity is shown by a bivariate correlation of .70 or more, or by a tolerance value of smaller than .10.

The third step is to conduct multiple regression analyses, one for each category separately, using the specific characteristics of the main categories which are found to be significant as independent variables and ISC as dependent variable. Correlational analyses are additionally computed to control for multicollinearity. To exclude the possibility that within the non-significant categories specific characteristics are significant, multiple regression analyses are also computed for the specific characteristics from the non-significant main categories.

Lastly, a regression analysis is conducted between all the significant characteristics found in the previous steps. A final model is established, including all the significant characteristics.

3 Results

3.1 Love and Basketball

As explained in the previous section, multiple steps are taken to assess which specific movie clip characteristics predict neural reliability.

First, eight new mean variables were computed, one for each category, resulting in the variables mean Emotion, mean Film techniques, mean Sounds, mean Objects, mean Setting, mean Movement, mean Weather and mean Interaction. Secondly, these eight variables together with the variables Music, Mean Entropy and Variation in Entropy were included in a correlation analysis in order to control for multicollinearity. The table with output for this correlation analysis can be found in Appendix C and shows the correlations between all of the above mentioned variables. Neither one of the variable pairs showed a correlation of .70 or higher, therefore a regression analysis could be conducted between the 11 variables and ISC. These 11 variables represented the independent variables and ISC represented the dependent variable.

Influence of the categories. Table 1 presents the results of this regression analysis. The main categories for Emotion, Film techniques, Weather, Interaction and Variation in Entropy are significant at a 1% level. From the significant main categories, the categories Weather and Interaction show a negative relation with ISC whereas the other variables depict a positive relationship. The characteristic Weather is only coded when there are outdoor scenes, therefore the negative relationship between Weather and ISC could imply that more outside scenes in the movie clip result in less ISC (i.e., less brain similarity across subjects). For the characteristic Interaction, this negative relationship could imply that when more interaction is displayed in the movie clip, brain similarity across subjects becomes less. For the other variables, being coded more is related to a larger ISC.

Table 1

Results of a regression analysis to predict ISC based on the eight categories, Music, Variation in Entropy and Mean Entropy

	Beta	t	Sig.	Tolerance
Music	-,045	-,701	,484	,791
MeanEntropy	,082	1,195	,233	,686
VarEntropy	,196	3,143	,002	,824
MEAN_Filmtechniques	,222	3,495	,001	,791
MEAN_Sounds	-,008	-,116	,908	,620
MEAN_Objects	,136	1,813	,071	,567
MEAN_Setting	,131	1,715	,088	,549
MEAN_Movement	-,118	-1,667	,097	,632
MEAN_Weather	-,200	-2,707	,007	,586

MEAN_Interaction	-,175	-2,793	,006	,809
MEAN_Emotion	,192	3,015	,003	,784

The mean variable Emotion shows a positive relation with ISC. However, there might be a difference between the influence of negative and positive emotions on ISC. To explore whether there is such a difference, the mean variable Emotion is split into two new mean variables, namely; mean Negative Emotion, which includes the characteristics negative, sad and anger, and mean Positive Emotion, which includes the characteristics positive and happy. A second regression was done, using the two new mean variables instead of the mean variable Emotion. The results of this regression are shown in Table 2. This table shows that, the new variable mean Positive Emotion is significant and shows a positive relation to ISC, whereas the variable mean Negative Emotion is not significant. Considering the significant positive mean variable Emotion, the significant mean variable Positive Emotion and the non-significant mean variable Negative Emotion, it could be concluded that the significance and positive relation of the mean variable mean Positive Emotion causes the significance and positive relation of the mean variable Emotion. From this conclusion it could be derived that there is a difference between positive and negative emotions in relation to ISC.

Table 2

Results of a regression analysis to predict ISC based on the seven categories, mean Positive Emotion, mean Negative Emotion, Music, Variation in Entropy and Mean Entropy

	Beta	t	Sig.	Tolerance
Music	-,047	-,743	,458	,791
MeanEntropy	,067	,993	,322	,689

VarEntropy	,179	2,910	,004	,820
MEAN_Filmtechniques	,271	4,201	,000	,749
MEAN_Sounds	,014	,194	,846	,612
MEAN_Objects	,150	2,015	,045	,562
MEAN_Setting	,100	1,317	,189	,538
MEAN_Movement	-,140	-1,980	,049	,624
MEAN_Weather	-,180	-2,449	,015	,579
MEAN_Interaction	-,152	-2,433	,016	,797
MEAN_Positive_Emotion	,308	3,867	,000	,490
MEAN_Negative_Emotion	-,120	-1,466	,144	,464

Influence of characteristics per category. The third step is to discover which specific characteristics in the significant main categories predict ISC the best. To this end, several standard multiple regressions were performed. The specific outcomes for each analysis can be found in Appendix C. The first regression includes all the characteristics from the main category Emotion. On the basis of the previous regression it can be assumed that the specific characteristics from the mean variable Positive Emotion appear to be significant. However, in this regression, only the characteristic Negative is significant at 5% level and has a negative relation with ISC. When a regression is performed between the characteristics Emotion, Positive, Happy and ISC, the three characteristics are not significant. This could indicate that other variables are correlating in such a way that positive emotions seem to predict ISC, but after further exploring this relation, no relationship is shown. The second regression includes all the characteristics from the main category Film techniques. Within this regression, the characteristics Cut, Edit and Overview are significant at 1% level and all have a positive relation with ISC. The third regression includes all the characteristics from the main category

Weather. Despite the former notice that this variable was significant, no significant specific characteristics were found. The fourth regression includes all the characteristics from the main category Interaction. As with the regression from the main category Weather, no significant specific characteristics were found. The fifth regression includes only the variable Variation Entropy. This characteristic predicts ISC at a 1% significance level and has a positive relation.

The fourth step is to discover if there are more significant characteristics which predict ISC within the non-significant main categories. The specific outcomes of these regressions can be found in Appendix C. The first regression is done with all the characteristics from the main category Sound. Within this regression no characteristics were found to be significant. The second regression includes the characteristics from the main category Object. The characteristic Bike is here significant at 1% level, the characteristics Vehicle and Food and drinks were automatically excluded from the regression by SPSS, due to their high correlations with other variables. From a correlational analysis between the characteristics from the main category Objects it appears that the characteristic Vehicle correlates highly with the characteristic Bike and the characteristic Food and drinks correlates highly with the characteristic Drinking glass. The third regression included all the characteristics from the main category Movement. The characteristic Dancing was significant at 5% level and the characteristic Hugging was significant at 1% level. The fourth regression included all the characteristics from the main category Setting. None of the characteristics in this regression showed to be significant. Regressions between the categories Music and ISC and Mean Entropy and ISC were both not significant.

To explore whether the non-significant main categories would significantly explain some unique variance in a regression with significant characteristics, a regression analysis was done in which all the previously found significant characteristics were included, and the non-significant main categories. The outcomes of this regression analysis can be found in

Appendix C. The non-significant main categories remained non-significant and were therefore not included in the final model.

Building the final model. Finally, a regression was done including all the characteristics that were found to be significant in the previous analyses. In this regression analysis the characteristic Negative was not significant and was therefore excluded from the model. The results for the final model are shown in Table 3 and include the characteristics Cut, Edit, Overview, Variation in Entropy, Hugging, Dancing and Bike. All the characteristics have a positive relation with ISC, so the more the characteristics is present the more ISC is displayed.

Table 3

Results of a regression analysis to predict ISC based on previously found significant characteristics

	Beta	T	Sig.	Tolerance
(Constant)		13,082	,000	
Cut	,397	6,784	,000	,785
Edit	,320	5,585	,000	,822
Overview	,113	2,127	,034	,962
VarEntropy	,139	2,583	,010	,931
Hugging	,130	2,467	,014	,977
Dancing	,121	2,321	,021	,996
Bike	,152	2,912	,004	,990

3.2 Gracie

For the movie clip of ‘Gracie’, the same procedure was followed as for the movie clip ‘Love and Basketball’. So, first eight mean variables were computed for the main categories, these categories are identical to the categories for the movie clip ‘Love and Basketball’. Also, a correlation analysis was conducted between the eight mean variables, Music, Mean Entropy and Variation Entropy, to control for multicollinearity. The results of this analysis can be found in Appendix D and show the correlation between all the previously mentioned variables. The variables Weather and Setting showed a correlation of .714, however, they were not excluded from further analyses.

Influence of the categories. Secondly, a regression analysis was conducted between the eight mean variables, Music, Mean Entropy, Variation Entropy and ISC, in which ISC was the dependent variable. The results of the analysis can be found in Table 4. From this table, it appears that the mean variables Movement, Weather, Mean Entropy, Variation Entropy and Music are significant. The significant category Movement shows a negative relation, whereas the other significant categories show a positive relation with ISC.

Table 4

Results of a regression analysis to predict ISC based on the eight categories, Music, Variation in Entropy and Mean Entropy

	Beta	t	Sig.	Tolerance
MEAN_Filmtechniques	,004	,053	,957	,635
MEAN_Sounds	-,023	-,400	,690	,893
MEAN_Objects	-,032	-,413	,680	,521
MEAN_Setting	-,050	-,530	,597	,346

MEAN_Movement	-,209	-3,004	,003	,627
MEAN_Weather	,282	3,296	,001	,414
MEAN_Interaction	,076	1,220	,224	,784
MEAN_Emotion	-,055	-,904	,367	,827
Music	,141	2,200	,029	,734
MeanEntropy	,317	4,209	,000	,535
VarEntropy	,241	4,027	,000	,850

The category Emotion shows a negative relation to ISC in this analysis. Despite the non-significance of this category, it is interesting to discover whether positive and negative emotions have a different effect on ISC. Therefore, the mean variable Emotion was split into two variables; mean Positive Emotion and mean Negative Emotion. The results of this analysis are shown in Table 5. The categories Positive Emotion and Negative Emotion are both not significant.

Table 5

Results of a regression analysis to predict ISC based on the seven categories, mean Positive Emotion, mean Negative Emotion, Music, Variation in Entropy and Mean Entropy

	Beta	t	Sig.	Tolerance
MEAN_Filmtechniques	,003	,036	,971	,620
MEAN_Sounds	-,023	-,386	,700	,874
MEAN_Objects	-,029	-,376	,707	,524
MEAN_Setting	-,052	-,549	,583	,346
MEAN_Movement	-,209	-2,993	,003	,622
MEAN_Weather	,281	3,234	,001	,405

MEAN_Interaction	,075	1,189	,236	,759
MEAN_Positive_Emotion	-,024	-,299	,765	,488
MEAN_Negative_Emotion	-,033	-,421	,674	,509
Music	,143	2,202	,029	,726
MeanEntropy	,318	4,180	,000	,527
VarEntropy	,241	4,026	,000	,847

Influence of characteristics per category. The third step is to discover which specific characteristics from the significant main categories are able to uniquely explain ISC best. In Appendix D the results of multiple regression analyses between the specific characteristics from each main category and ISC are presented. The first regression includes all the characteristics from the main category Movement. Despite the significant appearance of this category, none of the specific characteristics in the category are significant. The second regression includes the characteristics from the main category Weather. Within this regression, the characteristics Weather and Sunny are significant at 1% level and both show a positive relation with ISC. Regressions with the characteristics Mean Entropy and Music were both significant at 1% level and both showed a positive relation with ISC. A regression analysis with independent variable Variation in Entropy was significant at 5% level and had a positive relation with ISC.

The fourth step is to discover if there are more significant characteristics which predict ISC within the non-significant main categories. The specific outcomes of these regressions can be found in Appendix D. The first regression is done with the characteristics from the main category Film techniques. The characteristics Cut, Edit, Overview and Zooming in are significant at 1% level, and all show a positive relation to ISC. The second regression is conducted with the characteristics from the main category Emotion. None of the characteristics appeared to be significant. In a regression analysis with the characteristics from the category Sound, none of the characteristics was significant. The fourth regression included all the characteristics from the main category Objects. Within this regression, the characteristics Vehicle, Car and Sports gear were significant at a 1% level. The characteristic Soccer ball was significant at a 5% level. The characteristics Car and Soccer ball showed a negative relation with ISC. Despite this promising significant results, the characteristics Vehicle and Car showed a .001 Tolerance, which indicates multicollinearity. To resolve this problem, a mean variable of these two characteristics was computed. This mean variable was not found to be significant when replacing this variable for the variables Car and Vehicle in the same regression. The use of this new variable caused multicollinearity between the characteristics Food and drinks, Dinner, Breakfast, Dining table and Juice bottle. All these characteristics, except the characteristic Dinking table suddenly became significant. Therefore, a mean variable of these characteristics was computed and used in the same analysis. The mean variable did not appear to be significant. After the use of these new variables only the characteristic Sports gear remained significant at a 1% level with a positive relation to ISC. The fifth regression is done with the characteristics from the main category Setting. The characteristics Setting, Day and Unknown are significant at 1% level in this regression and all show a positive relation to ISC. The last regression is done with the characteristics from the main category Interaction. None of the characteristics within this category appeared to be significant.

Building the final model. Finally, a regression analysis was conducted between all the significant characteristics identified in earlier analyses and ISC. Within this regression, the characteristics Weather, Variation in Entropy, Music, Edit, Sports gear, Setting, Day and Unknown weather showed not to be significant. Therefore, an hierarchical regression analysis was conducted in which the most insignificant characteristic is at every turn removed from the analysis, until all characteristics are significant. The characteristics which remained significant were the characteristics Sunny, Mean Entropy, Cut, Edit, Overview, Zooming in and Setting. To make sure that no unique variance is explained by a category other than the categories represented by the characteristics previously described, a last analysis is done between the significant characteristics and the non-significant main categories. This analysis can be found in Appendix D. The main categories remained non-significant. Therefore, the final model, which is displayed in Table 6, consists of the characteristics Sunny, Mean Entropy, Cut, Edit, Overview, Zooming in and Setting. Only the characteristic Overview shows a negative relation with ISC, whereas the other characteristics show a positive relation with ISC.

Table 6

Results of a regression analysis to predict ISC based on previously found significant characteristics

	Beta	t	Sig.	Tolerance
(Constant)		-,974	,331	
Sunny	,127	2,024	,044	,708
MeanEntropy	,290	4,381	,000	,639
Cut	,254	4,541	,000	,899
Edit	,130	2,357	,019	,920
Overview	-,189	-3,425	,001	,918
Zooming.in	,158	2,970	,003	,990
Setting	,241	4,405	,000	,939

3.3 Comparison between the trailers

For both trailers the characteristics Cut, Edit and Overview are included in the final model. In both trailers Cut explains the most unique variance. Furthermore, the characteristic Overview shows a positive relation with ISC for the trailer ‘Love and Basketball’, whereas in the trailer ‘Gracie’ this characteristic shows a negative relation with ISC. Another difference between the results of the movie clips pertains to the influence of the entropy measures. Considering the trailer ‘Love and Basketball’, Variance in Entropy (positive relation) is included in the final model, whereas considering the trailer ‘Gracie’ Mean Entropy (positive relation) is included in the final model.

The final model from ‘Love and Basketball’ further includes the characteristics Hugging, Dancing and Bike. The characteristics Bike and Dancing do not appear in the trailer ‘Gracie’ and are therefore unable to appear in the final model of this trailer. The final model from ‘Gracie’ further includes the characteristics, Sunny, Zooming in, and Setting.

4 Discussion

4.1 Summary of the results

The aim of the present study was to investigate whether there is a relationship between specific movie clip characteristics and the evolution of neural reliability over time. Additionally, the study aimed to investigate which specific characteristics are able to predict neural reliability. Specific movie clip characteristics were assessed, using a codebook specifically made for the two trailers used for this study.

The results show that for the two trailers used in this study, different characteristics significantly contribute to the prediction of ISC. The majority of the significant predictors were included in the main category Film techniques. For both trailers the characteristic Cut showed to be the strongest predictor. This characteristic showed a positive relation to ISC in both trailers. An explanation for this finding could be that a cut, which relates to the shifting from one scene to another, is a clearly visible effect. Therefore, this shifting from one scene to another may cause similar brain activity across different individuals. Furthermore, within the trailer ‘Love and Basketball’ the characteristic Variation in Entropy shows a significant positive relation to ISC. This indicates that the more variation in entropy is displayed, within a time window, the more similar brain activity is elicited across subjects. This is an interesting finding, since the effect of Variation in Entropy has not yet been found in the literature. Within the trailer ‘Gracie’, Mean Entropy is found to have a significant positive relation to ISC. This indicates that a higher mean entropy relates to an increase in ISC. However, in general, less complex images should increase ISC. The current finding is therefore inconsistent with previously described studies about the influence of visual complexity on ISC. Furthermore, the appearance of more outdoor scenes in the trailer ‘Gracie’ showed to have an effect on neural reliability. Sunny scenes were in this trailer included in the final model (positive relation), whereas this characteristic was not significant in the trailer ‘Love and Basketball’. So, more sunny scenes may cause more similar brain activity. This effect may be enhanced by difference in balance between indoor and outdoor scenes in the trailers. Differences between the two trailers could have occurred because of the differences in content of the movie clips. Despite trying to compare two trailers which are highly similar, they show some fundamental differences.

4.2 Limitations of the study

Despite these interesting results, this study has several limitations. First, due to time issues, it was only possible to code and analyse two of the 18 movie clips. To get a more extensive and more comprehensive view of the effects of specific movie clip characteristics on neural reliability, it would be preferable to code and analyse all the 18 movie clips presented by Boksem and Smidts (2015). Secondly, EEG measurement may be unreliable, due to factors such as thickness of the skull (Klimesch, 1999). However, as explained previously, this study required data with a high temporal resolution for which EEG measurements suit best. Third, the method for measuring neural reliability may be considered as quite indirect and ad hoc. Despite this, it is currently the most accurate method for computing neural reliability. Fourth, there was only one individual who coded the movie clips at one time point. Therefore, the coding may be unreliable. Coding the movie clips with more individuals or at different time point could have increased the power of this study. Lastly, the way in which the codebook is constructed could influence the results of this study. The codebook is composed by one individual, having more individuals involved in the composition of the codebook may enhance the generalizability of the codebook.

4.3 Points for further study

To explore the effect of specific audio-visual characteristics on neural reliability more extensively in the future, research could focus on the effects of specific film techniques. Film techniques are shown in this study to contribute mostly to the explanation of the variation in neural reliability. Furthermore, the effects of visual complexity on neural reliability could be explored more in depth, as these findings are most surprising in the current study. Besides this, future studies could also focus on the location of synchronisation, using fMRI data. It could be that certain characteristics elicit synchronisation in certain brain areas. Future studies should take into account that, to enhance the power of the study, it is necessary to include more individuals in the coding process and to evaluate an extensive amount of audio-visual stimuli.

4.4 Concluding remark

Concluding, the results of this study are promising and surprising. The results show that specific audio-visual stimuli characteristics, mainly related to film technique characteristics, are able to predict neural reliability over time. This may contribute to future research into this topic.

References

Barnett, S. B., White, H. M., & Cerf, M. (n.d.). *Keep it simple stimuli: brain-vetted elements of movie trailers predict opening weekend ticket sales.* Unpublished manuscript, Northwestern University, United States of America.

Boksem, M. A., & Smidts, A. (2015). Brain responses to movie trailers predict individual preferences for movies and their population-wide commercial success. *Journal of Marketing Research, 52(4),* 482-492.

Deldjoo, Y., Elahi, M., Cremonesi, P., Garzotto, F., Piazzolla, P., & Quadrana, M. (2016). Content-based video recommendation system based on stylistic visual features. *Journal on Data Semantics, 5,* 99-113.

Dmochowski, J. P., Bezdek, M. A., Abelson, B. P., Johnson, J. S., Schumacher, E. H., & Parra, L. C. (2014). Audience preferences are predicted by temporal reliability of neural processing. *Nature Communications, 5,* 1-9.

Dmochowski, J. P., Sajda, P., Dias, J., & Parra, L. C. (2012). Correlated components of Ongoing EEG point to emotionally laden attention – A possible marker of engagement? *Frontiers in Human Neuroscience, 6,* 1-9.

Fox, E. (2008). *Emotion science: cognitive and neuroscientific approaches to understanding human emotions.* Basingstoke: Palgrave Macmillan.

Gazzaniga, M. S., Ivry, R. B., & Mangun, G. R. (2014). *Cognitive Neuroscience; The biology of the mind (3rd edition).* New York: Norton.

Geiger, S., & Reeves, B. (1993). The Effects of Scene Changes and Semantic Relatedness on Attention to Television. *Communication Research, 20(2),* 155-175.

Gray, P., & Bjorklund, D. F. (2014). *Psychology (seventh edition).* New York, Worth Publishers.

Hasson, U., Landesman, O., Knappmeyer, B., Vallines, I., Rubin, N., & Heeger, D. J. (2008). Neurocinematics: The neuroscience of film. *Projections, 2(1),* 1-26

Heine, S. J. (2015). *Cultural psychology (3rd edition).* New York: W.W. Norton.

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research Reviews, 29(2-3),* 169-195.

Lang, A., Bolls, P., Potter, R., & Kawahara, K. (1999). The effects of production pacing and arousing content on the information processing of television messages. *Journal of Broadcasting & Electronic Media, 43*(4), 451-475.

Macinnis, D. J., & Park, C. W. (1991). The Differential Role of Characteristics of Music on High- and Low- Involvement Consumers Processing of Ads. *Journal of Consumer Research, 18(2),* 161-173.

Mcintosh, W. D., Smith, S. M., Bazzini, D. G., & Mills, P. S. (1999). Alcohol in the Movies: Characteristics of Drinkers and Nondrinkers in Films From 1940 to 1989. *Journal of Applied Social Psychology, 29(6),* 1191-1199.

Nummenmaa, L., Glerean, E., Viinikainen, M., Jääskeläinen, I. P., Hari, R., & Sams, M. (2012). Emotions promote social interaction by synchronizing brain activity across individuals. *PNAS, 109,* 9599-9604.

Reeves, B., Thorson, E., Rothschild, M. L., Mcdonald, D., Hirsch, J., & Goldstein, R. (1985). Attention to television: intrastimulus effects of movement and scene changes on alpha variation over time. *International Journal of Neuroscience, 27(3-4),* 241-255.

Wittenburg, P., Brugman, H., Russel, A., Klassmann, A., & Sloetjes, H. (2006). ELAN: a Professional Framework for Multimodality Research. In: Proceedings of LREC 2006, Fifth International Conference on Language Resources and Evaluation.

Appendix A. Codebook tailor-made for the trailers ‘Grace’ and ‘Love and Basketball’

Characteristic	Scoring	Description	Image
Emotion	0/1 (absent/present)	Reactions to events and situations; Rapid onset and last for a short time period; Coordinated set of responses to a specific set of circumstances.	
○ Positive	0/1 (absent/present)		
• Happy	0/1 (absent/present)	Seeing a Duchene smile, hearing laughter. The feeling of pleasure and enjoyment	
○ Negative	0/1 (absent/present)		
• Anger	0/1 (absent/present)	Seeing a frown. The strong feeling of displeasure and belligerence	
• Fear	0/1 (absent/present)	Seeing high eyebrows, big eyes and open mouth. Distressing emotion due to a threat	
• Sad	0/1 (absent/present)	Crying, low eyebrows. Affected with or expressive of grief or unhappiness	
○ Unknown	0/1 (absent/present)	Neither a positive or negative emotion	

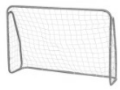
Characteristic	Scoring	Description
Film techniques		
• Cut	0/1 (absent/present)	When the camera cuts from one visual scene to the next visual scene; Unrelated scene changes
• Slow motion	0/1 (absent/present)	The slowing of real-life action through technical intervention
• Edit	0/1 (absent/present)	When the camera position changes, but the scene remains the same; Related scene changes
• Overview	0/1 (absent/present)	Broad view
• Close up	0/1 (absent/present)	Tightly framed person or object, including more detail
• Zooming in	0/1 (absent/present)	Continuously bring something into close up, while maintaining focus
• Zooming out	0/1 (absent/present)	Continuously decreasing the magnification of something, getting more overview

Characteristic	Scoring	Description
Interaction		
○ Verbal conversation	0/1 (absent/present)	Conversation by means of spoken words
• Normal message	0/1 (absent/present)	
• Question	0/1 (absent/present)	
• Shouting	0/1 (absent/present)	
○ Non-verbal conversation	0/1 (absent/present)	Conversation by means of gestures

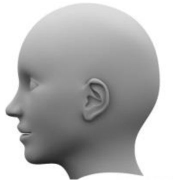
Characteristic	Scoring	Description
Weather		
• Sunny	0/1 (absent/present)	Lots of sunlight, clear sky
• Rainy	0/1 (absent/present)	Dark clouds, rain
• Unknown	0/1 (absent/present)	Night scene, neither sun or rain

Characteristic	Scoring
Sounds	
• Breaking glass	0/1 (absent/present)
• Cheering	0/1 (absent/present)
• Starting engine	0/1 (absent/present)
• Alarm clock	0/1 (absent/present)
• Shooting the ball	0/1 (absent/present)
• Bouncing with a ball	0/1 (absent/present)
• Scoring with a ball	0/1 (absent/present)

Characteristic	Scoring	Description
Music	0/1 (absent/present)	Hearing vocal and/or instrumental sounds arranged in a continuous way

Characteristic	Scoring	Description	Image
Objects			
○ Sports gear			
• Soccer ball	0/1 (absent/present)	White, black blocked inflated round object	
• Soccer goal	0/1 (absent/present)	Rectangular structure with two vertical posts supporting a horizontal post connected with a net, placed at the end of the soccer field	
• Soccer shoe	0/1 (absent/present)	Item of footwear worn when playing soccer	
• Basketball	0/1 (absent/present)	Brown/orange inflated round object with black lines	
• Basketball hoop	0/1 (absent/present)	Horizontal circular metal hoop supporting a net	
• Dumbbells	0/1 (absent/present)	Gymnastic apparatus consisting of two metal balls connected by a short bar serving as a handle	

• Towel	0/1 (absent/present)	Absorbent cloth, used for drying	
○ Vehicle			
• Car	0/1 (absent/present)	Road vehicle with four wheels	
• School bus	0/1 (absent/present)	Large vehicle used for transport of students	
• Bike	0/1 (absent/present)	Vehicle with two wheels in tandem, moved by pushing with feet on the pedals	
○ Food/Drinks			
• Dinner	0/1 (absent/present)	Evening meal	
• Breakfast	0/1 (absent/present)	First meal of the day	
• Dining table	0/1 (absent/present)	Table from which you have your meal	
• Drinking glass	0/1 (absent/present)	A container for holding liquids while drinking	
• Juice bottle	0/1 (absent/present)	A container with a neck that is narrower than the body and mouth, usually with a cap	
○ Body parts			

• Foot	0/1 (absent/present)	The part of the leg on which a person stands and moves, below the ankle	
• Hand	0/1 (absent/present)	Multi-fingered extremity at the end of the arm	
• Head	0/1 (absent/present)	Uppermost part of the body, containing brain, eyes, ears, nose, mouth and jaws	
○ Other			
• Bed	0/1 (absent/present)	Piece of furniture upon which a person sleeps	
• Alarm clock	0/1 (absent/present)	A clock that can be set to sound an alarm at any desired time	
• Cap	0/1 (absent/present)	Head covering with a curved part sticking out at the front	
• Money	0/1 (absent/present)	Medium of financial exchange	

Characteristic	Scoring	Description	Image
Setting			
• High school inside	0/1 (absent/present)	Long hall with lockers on each side	
• Soccer field	0/1 (absent/present)	Field of grass with white lines in a particular order and soccer goals at the end of the field	
• Inside front of a car	0/1 (absent/present)	Two seat, a steering wheel, dashboard	
• Day	0/1 (absent/present)	The time between sunrise and sunset	
• Night	0/1 (absent/present)	The period of darkness between sunset and sunrise	
• Basketball court outside	0/1 (absent/present)	Asphalt rectangle floor with white lines in a particular order with baskets at the end of the field	
• Basketball court inside	0/1 (absent/present)	Wooden rectangle floor with lines in a particular order and baskets at the end of	

		the field	
• Grandstand	0/1 (absent/present)	Main seating area of a stadium	
• Unknown	0/1 (absent/present)	Undefined setting	

Characteristic	Scoring	Description
Movement		
• Running	0/1 (absent/present)	Type of gait with an aerial phase, in which all feet are above the ground. Rapid movement
• Lying down	0/1 (absent/present)	To be in a horizontal position
• Walking	0/1 (absent/present)	One foot is always in contact with the ground, legs are kept mostly straight. Slow movement
• Kicking	0/1 (absent/present)	To extent one leg away from the body
• Turning	0/1 (absent/present)	Rotating
• Throwing	0/1 (absent/present)	To cause something to move out of your hand and through the air by quickly moving your arm forward
• Punching	0/1 (absent/present)	Thrusting blow with the fist
• Hugging	0/1 (absent/present)	To hold one closely in the arms. Embrace.
• Dancing	0/1 (absent/present)	To move rhythmically using prescribed or improvised steps and gestures
• Staring	0/1 (absent/present)	To look for a long time, often with your eyes wide open

• Dunking	0/1 (absent/present)	Type of basketball shot that is performed when a player jumps in the air and places the ball directly through the basket with one or both hands.
• Stripping	0/1 (absent/present)	To remove clothing
• Kissing	0/1 (absent/present)	The touch or pressing of one's lips against another person or object
• Bouncing	0/1 (absent/present)	To strike the ground and rebound
• Falling	0/1 (absent/present)	To suddenly drop down to a lower position, especially to leave a standing position, whether voluntarily or not
• Listening	0/1 (absent/present)	To give attention with the ear
• Pulling	0/1 (absent/present)	To apply force to something so as to cause motion towards the source of the force
• Yelling	0/1 (absent/present)	Speaking with a strong, loud, clear sound

Appendix B. Computation for neural reliability as presented in Dmochowski et al. (2012)

Neural reliability is computed by Dmochowski et al. (2012) as follows. For a given trailer, viewed by N subjects, there is a set of N data matrices $\{\boldsymbol{X_1}, \ldots, \boldsymbol{X_N}\}$. The spatiotemporal (i.e., electrodes by time) neural response of subject n $(n = \ 1, \ldots, N)$ is then conveyed by $\boldsymbol{X_n}$. After this, unique subject pairs are composed. This is done, using the following formula $\pi \ = \{\pi 1, \pi 2\} \ = \ \{(1,2), (1,3), \ldots, (N-1, N)\}$. Thus, the total number of unique pairs equals $P \ = \ N \ \times \ (N-1)/2$. Then, aggregated (across pairs) auto- and cross-covariance matrices are computed, using the formula below.

$$\boldsymbol{R_{11}} = \frac{1}{PT} \sum_{i=1}^{p} \boldsymbol{X}_{Pi1} \, \boldsymbol{X}_{Pi1}^{T},$$

$$\boldsymbol{R_{22}} = \frac{1}{PT} \sum_{i=1}^{p} \boldsymbol{X}_{Pi2} \, \boldsymbol{X}_{Pi2}^{T},$$

$$\boldsymbol{R_{12}} = \frac{1}{PT} \sum_{i=1}^{p} \boldsymbol{X}_{Pi1} \, \boldsymbol{X}_{Pi2}^{T},$$

where T in this computation is the number of time samples in $\boldsymbol{X_n}$ and ^{T} indicates matrix transposition.

The goal of the method of Dmochowski et al. (2014) is to find a projection vector $\boldsymbol{w}$ which maximizes the ISC between subject-aggregated data. This can be done by finding the $\boldsymbol{w}$ that maximizes the following formula $\frac{\boldsymbol{w}^T \boldsymbol{R_{12}} \boldsymbol{w}}{\sqrt{(\boldsymbol{w}^T \boldsymbol{R_{11}} \boldsymbol{w})(\boldsymbol{w}^T \boldsymbol{R_{22}} \boldsymbol{w})}}$. It is shown that assuming $\boldsymbol{w}^T \boldsymbol{R_{11}} \boldsymbol{w} = \boldsymbol{w}^T \boldsymbol{R_{22}} \boldsymbol{w}$ in the equation shown above, results in the following generalized eigenvalue problem, for which a standard solution exists:

$$\lambda(\boldsymbol{R_{11}} + \ \boldsymbol{R_{22}})\boldsymbol{w} = \ \boldsymbol{R_{22}} \boldsymbol{w}$$

In this equation, λ is the generalized eigenvalue corresponding to the maximal ISC elicited by the trailer, including all subject pairs. Eventually, neural reliability will be computed using the following formula: $neural\ reliability = \ \sum_{i=1}^{C} \lambda_i$.

Appendix C. Output regression analyses trailer 'Love and Basketball'

Table 1

Results of a correlational analysis between the eight categories, Mean Entropy, Variation in Entropy and Music

Correlations

		1	2	3	4	5	6	7	8	9	10	11
MEAN_Emotion (1)	Pearson Correlation	1										
MEAN_Filmtechniques(2)	Pearson Correlation	,108	1									
MEAN_Sounds (3)	Pearson Correlation	,016	-,188	1								
MEAN_Objects (4)	Pearson Correlation	-,146	-,061	,485	1							
MEAN_Setting (5)	Pearson Correlation	,228	,127	,343	,402	1						
MEAN_Movement (6)	Pearson Correlation	-,083	-,195	,403	,462	,146	1					
MEAN_Weather (7)	Pearson Correlation	,376	,301	,266	,141	,491	-,034	1				
MEAN_Interaction (8)	Pearson Correlation	,173	,188	,004	-,024	,318	-,185	,153	1			
MeanEntropy (9)	Pearson Correlation	-,063	,100	,103	,299	,247	,337	,031	,089	1		

VarEntropy (10)	Pearson Correlation	-,034	-,071	,047	,030	-,030	-,016	,021	-,077	-,278	1	
Music (11)	Pearson Correlation	,057	,058	,032	,100	,119	,090	,028	,112	,349	-,365	1

Table 2

Results of a regression analysis to predict ISC based on all characteristics from the category Emotion

	Beta	t	Sig.	Tolerance
Emotion	,413	1,680	,094	,057
Positive	-,131	-,768	,443	,119
Happy	,053	,537	,592	,358
Negative	-,392	-2,297	,022	,119
Anger	,103	1,469	,143	,706
Sad	,033	,510	,610	,851
Unknown	-,142	-,870	,385	,130

Table 3

Results of a regression analysis to predict ISC based on all characteristics from the category Film techniques

	Beta	t	Sig.	Tolerance
Film.techniques	,054	1,003	,317	,985
Cut	,454	7,676	,000	,820
Edit	,305	5,091	,000	,799
Close.up	,106	1,920	,056	,940

Overview	,139	2,562	,011	,971
Zooming.in	-,010	-,178	,859	,988
Zooming.out	-,058	-1,071	,285	,975

Table 4

Results of a regression analysis to predict ISC based on all characteristics from the category Weather

	Beta	t	Sig.	Tolerance
Weather	,631	,731	,466	,005
Sunny	-,516	-,726	,469	,007
Unknown.weather	-,457	-,726	,468	,009

Table 5

Results of a regression analysis to predict ISC based on all characteristics from the category Interaction

	Beta	T	Sig.	Tolerance
Interaction	-,048	-,072	,942	,008
Verbal.conversation	-,036	-,054	,957	,008

Table 6

Results of a regression analysis to predict ISC based on Variation in Entropy

	Beta	t	Sig.	Tolerance
VarEntropy	,178	3,013	,003	1,000

Table 7

Results of a regression analysis to predict ISC based on all characteristics from the category Sound

	Beta	t	Sig.	Tolerance
Sounds	,122	,802	,423	,157
Bouncing.with.a.ball	-,144	-,991	,323	,170
Scoring.with.a.ball	-,037	-,532	,595	,734
Shooting.the.ball	,002	,027	,979	,765

Table 8

Results of a regression analysis to predict ISC based on all characteristics from the category Objects

	Beta	t	Sig.	Tolerance
Objects	,090	1,523	,129	,992
Sports.gear	,388	1,837	,067	,077
Basketball	-,345	-1,706	,089	,085
Basketball.hoop	-,023	-,315	,753	,673
Bike	,171	2,858	,005	,969
Drinking.glass	,080	1,350	,178	,996
Cap	-,052	-,867	,387	,968

Table 9

Results of a regression analysis to predict ISC based on all characteristics from the category Movements

	Beta	t	Sig.	Tolerance
Movement	-,089	-1,034	,302	,458
Bouncing	,052	,782	,435	,768
Dancing	,133	2,246	,026	,977
Dunking	,025	,418	,677	,924
Falling	-,089	-1,390	,166	,835
Hugging	,166	2,708	,007	,908
Kissing	,034	,560	,576	,934
Listening	,093	1,550	,122	,945
Punching	,072	1,221	,223	,991
Running	-,074	-1,169	,243	,851
Stripping	,024	,394	,694	,912
Throwing	,000	-,001	,999	,776
Turning	,086	1,380	,169	,880
Walking	-,047	-,743	,458	,859
Pulling	-,031	-,509	,611	,952

Table 10

Results of a regression analysis to predict ISC based on all characteristics from the category Setting

	Beta	t	Sig.	Tolerance
Setting	,094	1,484	,139	,871
Basketball.court.inside	,149	1,645	,101	,431
Basketball.court.outside	,103	,970	,333	,315
Grandstand	-,060	-,957	,339	,897
Inside.front.of.a.car	-,037	-,561	,575	,802
Night	,113	1,304	,193	,470
Day	,012	,100	,920	,237
Unknown.setting	,178	1,952	,052	,425

Table 11

Results of a regression analysis to predict ISC based on Music

	Beta	t	Sig.	Tolerance
Music	-,071	-1,179	,239	1,000

Table 12

Results of a regression analysis to predict ISC based on Mean Entropy

	Beta	t	Sig.	Tolerance
MeanEntropy	,032	,531	,596	1,000

Table 13

Results of a regression analysis to predict ISC based on all previously found significant characteristics and the non-significant categories

	Beta	t	Sig.	Tolerance
MEAN_Interaction	-,014	-,238	,812	,773
MEAN_Emotion	,091	1,520	,130	,766
MEAN_Weather	-,020	-,334	,739	,792
Cut	,426	7,163	,000	,781
Edit	,314	5,248	,000	,772
Overview	,139	2,602	,010	,961
Hugging	,106	1,964	,051	,939
Dancing	,096	1,764	,079	,930
Bike	,140	2,528	,012	,897

Appendix D. Output regression analysis trailer 'Gracie'

Table 1

Results of a correlational analysis between the eight categories, Mean Entropy, Variation in Entropy and Music

Correlations

		1	2	3	4	5	6	7	8	9	10	11
MEAN_Emotion (1)	Pearson Correlation	1										
MEAN_Filmtechniques(2)	Pearson Correlation	,154	1									
MEAN_Sounds (3)	Pearson Correlation	-,048	,119	1								
MEAN_Objects (4)	Pearson Correlation	-,301	-,036	,178	1							
MEAN_Setting (5)	Pearson Correlation	,045	,323	,145	,524	1						
MEAN_Movement (6)	Pearson Correlation	-,089	-,105	,064	,403	,402	1					
MEAN_Weather (7)	Pearson Correlation	,039	,311	,132	,401	,714	,429	1				
MEAN_Interaction (8)	Pearson Correlation	,155	,257	-,167	,049	,286	,190	,314	1			

MeanEntropy (9)	Pearson Correlation	,060	,372	,124	,415	,569	,393	,422	,268	1		
VarEntropy (10)	Pearson Correlation	-,018	-,028	-,118	-,305	-,311	-,172	-,211	-,079	-,231	1	
Music (11)	Pearson Correlation	,038	,257	,094	,212	,415	,285	,471	,226	,336	-,079	1

Table 2

Results of a regression analysis to predict ISC based on all characteristics from the category Movement

	Beta	t	Sig.	Tolerance
Movement	,132	1,788	,075	,722
Hugging	-,061	-,962	,337	,959
Kicking	-,092	-1,373	,171	,868
Listening	-,092	-1,426	,155	,948
Lying.down	-,096	-1,526	,128	,992
Turning	,030	,483	,630	,989
Running	,019	,289	,773	,910
Walking	-,127	-1,842	,067	,821

Table 3

Results of a regression analysis to predict ISC based on all characteristics from the category Weather

	Beta	t	Sig.	Tolerance
Weather	,283	4,722	,000	,933
Sunny	,269	3,960	,000	,728
Rainy	,085	1,352	,178	,842
Unknown.weather	,034	,510	,610	,733

Table 4

Results of a regression analysis to predict ISC based on Mean Entropy

	Beta	t	Sig.	Tolerance
MeanEntropy	,320	5,365	,000	1,000

Table 5

Results of a regression analysis to predict ISC based on Music

	Beta	t	Sig.	Tolerance
Music	,289	4,791	,000	1,000

Table 6

Results of a regression analysis to predict ISC based on Variation in Entropy

	Beta	t	Sig.	Tolerance
VarEntropy	,156	2,511	,013	1,000

Table 7

Results of a regression analysis to predict ISC based on all characteristics from the category Film techniques

	Beta	t	Sig.	Tolerance
Film.techniques	,010	,170	,865	,954
Cut	,222	3,594	,000	,905
Edit	,165	2,686	,008	,914
Overview	-,044	-,705	,482	,880
Close.up	,258	4,206	,000	,918
Zooming.in	,200	3,375	,001	,983
Zooming.out	,036	,605	,546	,988

Table 8

Results of a regression analysis to predict ISC based on all characteristics from the category Emotion

	Beta	t	Sig.	Tolerance
Emotion	,060	,611	,542	,405
Positive	-,054	-,588	,557	,469
Happy	,056	,806	,421	,821
Negative	,122	,898	,370	,215
Anger	-,018	-,209	,835	,515
Sad	-,208	-1,935	,054	,343

Table 9

Results of a regression analysis to predict ISC based on all characteristics from the category Sounds

	Beta	t	Sig.	Tolerance
Sounds	,404	,970	,333	,022
Alarm.clock	-,146	-,819	,414	,122
Cheering	-,402	-1,151	,251	,032
Breaking.glass	,052	,528	,598	,395
Shooting.the.ball	-,123	-1,754	,081	,785
Starting.engine	-,068	-,398	,691	,131

Table 10

Results of a regression analysis to predict ISC based on all characteristics from the category Objects

	Beta	t	Sig.	Tolerance
Objects	,038	,633	,528	,977
Sports.gear	,338	2,901	,004	,259
Soccer.ball	-,226	-2,293	,023	,362
Soccer.goal	-,117	-1,590	,113	,654
Soccer.shoe	,088	1,283	,201	,742
Dumbbels	-,041	-,628	,530	,829
Towel	,008	,129	,898	,831
Vehicle	8,506	4,457	,000	,001
Car	-8,490	-4,462	,000	,001
School.bus	,064	1,042	,298	,924

Dinner	-1,477	-,879	,380	,001
Breakfast	-2,332	-,918	,359	,001
Dining.table	2,744	,906	,366	,000
Juice.bottle	,108	1,573	,117	,749
Hand	-,024	-,199	,843	,239
Bed	-,019	-,310	,757	,892
Alarm.clock.object	,044	,681	,496	,851
Money	-,037	-,326	,745	,270

Table 11

Results of a regression analysis to predict ISC based on characteristics from the category Objects, replacing the characteristics Vehicle and Car for the mean variable Vehicle_Car

	Beta	t	Sig.	Tolerance
Objects	,044	,718	,473	,978
Sports.gear	,341	2,847	,005	,259
Soccer.ball	-,186	-1,854	,065	,366
Soccer.goal	-,138	-1,839	,067	,658
Soccer.shoe	,070	,994	,321	,746
Dumbbels	-,042	-,632	,528	,829
Towel	,007	,106	,916	,831
School.bus	,085	1,352	,178	,929
Food.and.drinks	14,529	2,617	,009	,000
Dinner	-6,042	-2,467	,014	,001
Breakfast	-9,022	-2,476	,014	,000
Dining.table	2,757	,887	,376	,000

Juice.bottle	-12,152	-2,581	,010	,000
Hand	,011	,086	,931	,240
Bed	-,023	-,360	,719	,892
Alarm.clock.object	,038	,578	,564	,852
Money	-,080	-,681	,497	,271
MEAN_Vehicle_Car	-,013	-,172	,864	,617

Table 12

Results of a regression analysis to predict ISC based on characteristics from the category Objects, replacing the variables Food and drinks, Dinner, Dining table, Breakfast and Juice bottle for a mean of these variables

	Beta	t	Sig.	Tolerance
Objects	,051	,822	,412	,981
Sports.gear	,345	2,841	,005	,259
Soccer.ball	-,159	-1,558	,121	,369
Soccer.goal	-,151	-1,978	,049	,661
Soccer.shoe	,059	,827	,409	,748
Dumbbels	-,042	-,618	,537	,829
Towel	,007	,107	,915	,831
School.bus	,072	1,129	,260	,937
Hand	-,021	-,164	,870	,244
Bed	-,019	-,287	,774	,894
Alarm.clock.object	,042	,623	,534	,853
Money	-,067	-,569	,570	,272
MEAN_Vehicle_Car	,045	,620	,536	,721

MEAN_Foodanddrinks_ Dinner_Breakfast_Dinin gtable_Juicebottle	,104	1,602	,110	,907

Table 13

Results of a regression analysis to predict ISC based on all characteristics from the category Setting

	Beta	t	Sig.	Tolerance
Setting	,273	4,429	,000	,889
High.school.inside	-,099	-1,652	,100	,946
Inside.front.of.a.car	-,054	-,907	,365	,965
Grandstand	,012	,207	,837	,961
Day	,251	3,004	,003	,485
Night	,083	1,021	,308	,509
Soccer.field	-,046	-,686	,493	,767
Unknown.setting	,166	2,742	,007	,920

Table 14

Results of a regression analysis to predict ISC based on all characteristics from the category Interaction

	Beta	t	Sig.	Tolerance
Interaction	,635	1,097	,274	,011
Verbal.conversation	-,468	-,810	,419	,011
Shouting	,112	1,789	,075	,973
Question	,084	1,362	,174	,993

Normal.message	-,029	-,463	,644	,988

Table 15

Results of a regression analysis to predict ISC based on all previously found significant characteristics

	Beta	t	Sig.	Tolerance
Weather	-,802	-,763	,446	,003
Sunny	,195	2,141	,033	,339
MeanEntropy	,312	4,276	,000	,527
VarEntropy	,113	1,465	,144	,474
Music	,031	,380	,704	,435
Cut	,189	2,357	,019	,439
Edit	,104	1,720	,087	,774
Overview	-,201	-3,579	,000	,888
Zooming.in	,152	2,804	,005	,954
Sports.gear	,050	,850	,396	,821
Setting	1,020	,963	,337	,003
Day	-,100	-1,063	,289	,315
Unknown.weather	,013	,209	,835	,702

Table 16

Results of a regression analysis to predict ISC based on all previously found significant characteristics and the non-significant categories

	Beta	t	Sig.	Tolerance
Sunny	,177	2,547	,011	,576
MeanEntropy	,302	4,188	,000	,534
Cut	,229	3,974	,000	,832
Edit	,126	2,282	,023	,907
Overview	-,202	-3,315	,001	,748
Zooming.in	,169	3,092	,002	,929
Setting	,238	4,168	,000	,850
MEAN_Emotion	-,037	-,619	,537	,789
MEAN_Sounds	,103	1,652	,100	,709
MEAN_Objects	-,092	-1,295	,197	,546
MEAN_Movement	-,083	-1,330	,185	,709
MEAN_Interaction	,078	1,333	,184	,806