ΔΙΑΤΜΗΜΑΤΙΚΟ ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ στα

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ΜΕΤΑΠΤΥΧΙΑΚΗ ΔΙΠΛΩΜΑΤΙΚΗ ΕΡΓΑΣΙΑ

Τίτλος Εργασίας

Ανάλυση και σύγκριση πολύπλοκων δικτύων του εγκεφάλου σε άτομα με ή χωρίς μαθηματικό άγχος κατά την μαθηματική επεξεργασία.

Analysis and comparison of complex brain networks in math anxious and non math-anxious individuals during math performance.

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ΕΠΙΒΛΕΠΩΝ: Παναγιώτης Μπαμίδης, Αν. Καθηγητής Α.Π.Θ.

Θεσσαλονίκη , Δεκέμβριος 2016

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Θεσσαλονίκη , Δεκέμβριος 2016

Ευχαριστίες

Θα ήθελα να ευχαριστήσω τον επιβλέποντα καθηγητή , κύριο Μπαμίδη Παναγιώτη για τη βοήθεια και τις πολύτιμες γνώσεις που μου προσέφερε σχετικά με τη Επιστήμη του Εγκεφάλου και τις εφαρμογές των Μαθηματικών στην έρευνα για τον Εγκέφαλο. Θα ήθελα, ακόμη, να ευχαριστήσω τον καθηγητή κύριο Αντωνίου Ιωάννη, για την πολύτιμη καθοδήγησή του και τη βοήθεια που μου προσέφερε σε όλη την πορεία της εργασίας μου, καθώς και για τις γνώσεις που μου προσέφερε σε όλη τη διάρκεια των Μεταπτυχιακών μου σπουδών. Τέλος, θα ήθελα να ευχαριστήσω τον Δρ Μανούσο Κλάδο, που μου προσέφερε, επίσης πολύτιμα εργαλεία, γνώσεις και καθοδήγηση για να περιηγηθώ σε ασφαλή μονοπάτια στη Νευρο-επιστήμη. Τέλος, επιθυμώ να ευχαριστήσω την οικογένειά μου, χάρις στους οποίους έγινα ο άνθρωπος που είμαι και χωρίς τους οποίους δεν θα είχα καταφέρει να προχωρήσω στη ζωή μου.

Abstract :

The current study aims to provide a literature review about math anxiety. Furthermore, the brain activation network of individuals, regarding their math-anxiety during the processing of arithmetic calculations and a working memory task is demonstrated. Data were obtained from university students through EEG recordings. The brain networks are constructed for each kind of brainwaves (Alpha 1, Alpha 2, Beta, Gamma, Delta, Theta). For the construction of the links of the networks, we use imaginary part of coherence as a metric.
Based on previous network visualizations, some useful network measures such as degree centrality, betweeness centrality, density, characteristic path length, eigenvector centrality, transitivity, clustering coefficient and efficiency (local & global) are computed.
Analysis of the results is expected to shed light on the organization of the cortical networks and on the interactions that occur in the brain of math-anxious and non math-anxious individuals and influence the efficiency (global and average local) and the density of their brain network.
Finally, we cite some interesting connections of Neuroscience and Economics and we propose some interesting research directions that occured during this study.

Key words :
math anxiety, working memory, networks, brain connectivity, global efficiency, local efficiency, density

Περιεχόμενα

Σύνοψη

Το παρόν πόνημα, αποσκοπεί αρχικά στο να συγκεντρώσει μέσω βιβλιογραφικής ανασκόπησης τα αποτελέσματα διαφόρων ερευνών σχετικά με το μαθηματικό άγχος και τις επιδράσεις που αυτό μπορεί να έχει σε διάφορους τομείς της ζωής των ατόμων που το βιώνουν. Επιπλέον σκοπός της εργασίας είναι να υπολογιστούν διάφορες μετρικές στα δίκτυα του εγκεφάλου ατόμων με ή χωρίς μαθηματικό άγχος καθώς τα άτομα αυτά υποβάλλονται σε τεστ για την μνημη εργασίας κατά τη διάρκεια μαθηματικής επεξεργασίας, και στη συνέχεια να μελετηθεί η επίδραση του μαθηματικού άγχους και της αυξανόμενης δυσκολίας των τεστ της μνημη εργασίας σε μετρικές όπως η αποτελεσματικότητα (efficiency) του δικτύου (τοπική και καθολική) και η πυκνότητα του δικτύου.

Στο **πρώτο** κεφάλαιο παρουσιάζεται το υπόβαθρο στο οποίο στηρίζεται η παρούσα εργασία, ο σκοπός της εργασίας, ο τρόπος συλλογής των δεδομένων, η μεθοδολογία της έρευνας και επεξηγήσεις των βασικών εννοιών που θα χρησιμοποιηθούν στα επόμενα κεφάλαια. Το μαθηματικό άγχος ορίζεται ως ένα αίσθημα έντασης, ανυπομονησίας, ή φόβου που σχετίζεται με την απόδοση στα Μαθηματικά. Η "μνημη εργασίας" του εγκεφάλου ορίζεται ως ένα γνωστικό σύστημα με περιορισμένη χωρητικότητα που είναι υπεύθυνο για την διατήρηση, επεξεργασία και διαχείριση της πληροφορίας. Η "μνημη εργασίας", θεωρείται ως η βασική αιτία της λογικής και επιχειρηματολογίας, της συμπεριφοράς και της λήψης αποφάσεων. Το μαθηματικό άγχος και οι εργασίες της "τρέχουσας μνήμης" αποτελούν τους βασικούς παράγοντες που χρησιμοποιήθηκαν στη λήψη των δεδομένων μας. Τα δεδομένα ελήφθησαν από την εργασία "**ERP Measures of Math Anxiety: How Math Anxiety Affects Working Memory and Mental Calculation Tasks?"** των Κλάδου, Σίμου, Μιχελογιάννη, Margulies και Μπαμίδη (Klados et. al, 2015). Η συλλογή των δεδομένων έγινε μέσω εγκεφαλοφραφήματος σε φοιτητές κατά τη διάρκεια της επίλυσης 4 διαφορετικών μαθηματικών εργασιών (πρόσθεση μεταξύ μονοψήφιων αριθμών, πρόσθεση μεταξύ διψήφιων αριθμών, πολλαπλασιασμός μονοψήφιων, πολλαπλασιασμός διψήφιων) και κατά την διεκπεραίωση εργασιών της "τρέχουσας μνήμης" με τρία επίπεδα αυξανόμενης

δυσκολίας. Το μαθηματικό άγχος υπολογίστηκε για κάθε συμμετέχοντα βάσει προσωπικών του καταθέσεων. Για την κατασκευή των συνδέσεων μεταξύ των κόμβων των δικτύων χρησιμοποιήθηκε ως μετρική το imaginary part of coherence, κύρίως λόγω της αμεροληψίας του έναντι τν πηγών και της απεικόνισης μόνο των πραγματικών σχέσεων μεταξύ τους. Τέλος, ορίζονται τα εγκεφαλικά κύματα, που απεικονίζουν την ηλεκτρική δραστηριότητα των εκατομμυρίων νευρώνων του εγκεφάλου, και ορίζονται τα βασικά χαρακτηριστικά για κάθε ένα από τα πέντε βασικά είδη εγκεφαλικών κυμάτων (άλφα, βήτα, γάμμα, δέλτα, θήτα).

Στο **δεύτερο** κεφάλαιο παρουσιάζονται τα αποτελέσματα διαφόρων ερευνών σχετικά με το μαθηματικό άγχος και την επίδρασή του σε διάφορους τομείς όπως στην εκπαίδευση, σε πτυχές της συμπεριφοράς, της κοινωνικής ζωής, της συναισθηματικής νοημοσύνης, της πρόκλησης πόνου, ακόμα και των αγοραστικών επιλογών των ατόμων που βιώνουν την επίδραση του μαθηματικού άγχους.

Στο **τρίτο** κεφάλαιο παρουσιάζονται βασικοί ορισμοί και έννοιες που αφορούν τη συνδεσιμότητα του εγκεφάλου καθώς και έννοιες και εργαλεία της θεωρίας δικτύων που χρησιμοποιούνται για την ανάλυση του δικτύου του εγκεφάλου. Αναφέρονται συνοπτικά τα είδη της συνδεσιμότητας του εγκεφάλου : η δομική συνδεσιμότητα, όπου οι συνδέσεις του δικτύου αναφέρονται κυρίως σε ανατομικά χαρακτηριστικά όπως οι προεκτάσεις της λευκής ουσίας , η λειτουργική συνδεσιμότητα όπου οι συνδέσεις ενώνουν απομακρυσμένες περιοχές που έχουν κάποια λειτουργική συσχέτιση(π.χ. ενεργοποιούνται ταυτόχρονα για κάποιο σκοπό) και η αποτελεσματική συνδεσιμότητα, στην οποία οι συνδέσεις του δικτύου έχουν κατεύθυνση και έχουν την έννοια της αιτιότητας (μελετάνε τι προκαλεί μία περιοχή σε μία άλλη). Ακόμη, ορίζονται βασικές μετρικές των δικτύων, όπως η βαθμική κεντρικότητα, η ενδιάμεση κεντρικότητα, η κεντρικότητα ιδιοδιανυσμάτων, η δομικότητα, ο συντελεστής σύμπλεξης, το μέσο μήκος μονοπατιού, η διάμετρος, η εκκεντρότητα, η πυκνότητα, η ιδιότητα μικρόκοσμου και η αποτελεσματικότητα σε τοπικό και καθολικό επίπεδο.

Στο **τέταρτο** Κεφάλαιο παρουσιάζεται η μεθοδολογία της έρευνας. Αρχικά τα 576 δίκτυα (για κάθε άτομο, για κάθε τεστ της τρέχουσας μνήμης, και για κάθε ρυθμό) και οι μετρικές τους υπολογίστηκαν σε Matlab, με το Brain Connectivity toolbox. Στη συνέχεια, πήραμε τις τιμές για το local efficiency, global efficiency και density, τις

μετασχηματίσαμε κατάλληλα και τις περάσαμε σε SPSS για να κάνουμε ANOVA και να διαπιστώσουμε την επίδραση του μαθηματικού άγχους και της δυσκολίας στα τεστ αυξανόμενης δυσκολίας της τρέχουσας μνήμης στις μετρικές που επιλέξαμε.
Στο **πέμπτο** παρουσιάζονται συνοπτικά τα αποτελέσματα της ανάλυσης με το SPSS. Τα αναλυτικά αποτελέσματα υπάρχον στο Appendix A. Πιο ειδικά, στατιστικά σημαντικά αποτελέσματα έδωσε το Average local efficiency, το οποίο φάνηκε να επηρεάζεται από το μαθηματικό άγχος και τα τεστ αυξανόμενης δυσκολίας της τρέχουσας μνήμης.
Τα συμπεράσματα που προκύπτουν από την εργασία, τα ανοικτά ερωτήματα και προτάσεις για περαιτέρω έρευνα, παρουσιάζονται στο **έκτο** Κεφάλαιο.
Τέλος, στο πρώτο Παράρτημα καταγράφονται κάποιες ενδιαφέρουσες συνδέσεις της Νευροεπιστήμης με τα Οικονομικά, ενώ στο Δεύτερο Παράρτημα παρατίθενται αναλυτικά τα αποτελέσματα της έρευνας.

Chapter 1

Introduction

Background for this study

Effects of math anxiety on ERP amplitude during performance of arithmetic calculations and working memory tasks are investigated in various studies (Klados et. al, 2015). Math anxiety has been proven to play an important role in many aspects of an anxious individual's life, concerning their school performance, their emotional intelligence, their social life, their career paths, and even their behavior, personality and choices. In the current study, we are going to record the various aspects of math anxiety, as indicated by literature, and then investigate the influence of math anxiety and difficulty in working memory tasks on some network metrics (global efficiency, average local efficiency and density).

Data acquisition and brief results:

The data were taken from the paper of Klados et. al. (2015). Data (576 datasets of 52x52 matrices) were obtained from university students during the processing of solving four types of arithmetic problems (one and two-digit addition and multiplication) and a working memory task comprised of three levels of difficulty (1,2,and 3-back task). The emphasis is on anxiety within normal populations rather than within clinically anxious ones. Compared to the Low-MA group, High-MA individuals demonstrated reduced ERP amplitude at frontocentral (between 180-320 ms) and centroparietal locations (between 380-420 ms). These effects were not relevant to how hard or complex a task was, how each individual performed, and how high were their levels of general state/trait anxiety. Results support the theory that high levels of self-reported math anxiety are related with lower cortical activation during the first stages of the execution of numeric stimuli as far as cognitive tasks are concerned (Klados et. al, 2013)

Purpose of the study-Problem-Solution

We report some views about math anxiety and various aspects of a person's life, and demonstrate the brain activation network of individuals, regarding their "math-anxiety"(positive/negative) during a concrete working memory task, as well as research the effect of math anxiety and working memory tasks on network metrics (global efficiency, average local efficiency and density).

Problem: lack of a review record about facts relevant to math anxiety and investigation about how math anxiety and difficulty in back tests of the working memory influence the efficiency (global and local) and the density of the brain network of individuals.

Solution: collection of chosen literature about math anxiety and analysis of data about density, global efficiency and local efficiency to understand whether math anxiety and difficulty in back tests play an important role on the values of these metrics.

Math anxiety:

Anxiety is an aversive emotional and motivational state occurring in threatening circumstances. (Eysenck et. al) Math anxiety is a phenomenon that is often considered when examining students' problems in mathematics. Mark H. Ashcraft defines math anxiety as "a feeling of tension, apprehension, or fear that interferes with math performance" (Ashcraft, 2002). The first math anxiety measurement scale was developed by Richardson and Suinn in 1972. According to Hembree, math anxiety is positively correlated with avoidance of math and is related to poor math performance on math achievement tests and negative attitudes concerning math.

What is more, Ashcraft found that there is an inverse relationship between math anxiety and confidence and motivation. Ashcraft administered a test that was increasingly getting more mathematically challenging, and pointed out that most of the students do well on the first part of the test which measures performance, even the highly math-anxious ones. On the other hand, on the latter and more difficult part of the test, Ashcraft noticed a stronger negative correlation between math anxiety and accuracy of the responses. Sian Beilock and her group (2011) determined that math anxiety is not simply about being bad at math. They confirmed, after the examination of brain scans, that math anxiety is actually caused by the anticipation or the thought of solving math. Their research through the brain scans showed that the brain area that is triggered when someone experiences math anxiety overlaps the same area of the brain where body harm is located. That means, highly math anxious individuals, are possibly feeling body pain when their anxiety is triggered. People's fear of math is, also, related to test taking and performance anxiety. Some researchers have suggested a high correlation between math anxiety and math performance.

Richardson and Suinn (1972) defined mathematical anxiety as "feelings of apprehension and tension concerning manipulation of numbers and completion of mathematical problems in various contexts".

In Klados paper, math anxiety is measured as a self-reported measure. The tool they used in order to measure anxiety was the abbreviated version of AMAS, that consists of nine items representing common situations faced by students (e.g., “Thinking about an upcoming math test one day before” and “Starting a new chapter in a math book”; Hopko et al. 2003). Participants were asked to rate the level of anxiety associated with each situation on a 5-point Likert scale with 45 points as a maximum score for anxiety (Klados et. al (2013))

Working memory :

Working memory, a core executive function, is a cognitive system with a limited capacity that is responsible for the transient holding, processing, and manipulation of information (en.wikipedia.org).

Working memory is considered to be the leading process behind reasoning, decision making and behavior. It is a system for temporarily storing and managing the information required to carry out complex cognitive tasks such as learning, reasoning, and comprehension.

Working memory is often mistaken as short-term memory, however neuroscientists declare that the two memory processes seem to be distinct, given the fact that they arise from different neural subsystems in the prefrontal cortex. Working memory is responsible for the manipulation of information, while short-term memory is involved in the short-term storage of information.

Working memory, keeps and manipulates incoming inputs and incorporates it with other information storage in long-term memory in order to use it in novel conditions. This process is necessary for fundamental aspects of usual activities such as learning, reasoning, and reading skills (Baddeley, 1986) as well as goal directed behavior. Goal directed behavior consists of keeping relevant information in mind (working memory) and irrelevant information out of mind (behavioral inhibition or inference resolution). Research implies that working memory and inference resolution are functions based on the prefrontal cortex (Bunge et. al, 2001)

In the study of Klados et. al (2013), all participants underwent a working memory task (N-back with three levels of load/difficulty) and four arithmetic tasks (Single Digit Addition, Double-Digit Addition, Single Digit Multiplication, and Double-Digit Multiplication). In the one-back condition participants were asked to press the left mouse button to indicate that the current stimulus (single digit) was the same with the immediately preceding one and the right button for a "No" answer. In the two- and three back conditions, participants compared the current stimulus with other preceding stimuli, either two or three positions before, respectively. A total of 40 trials (single digit numbers) were presented in each n-back condition (Klados et al, 2013)

State versus Trait anxiety

State anxiety is defined as the result of a disturbing stimulus that leads to a temporary annoying emotional arousal. Usually, state anxiety appears due to unpleasant event and the person experiences symptoms of state anxiety as a reaction to deal with the situation.

Trait anxiety is the situation when people often tend to worry excessively about future events. It differs from state anxiety in its intensity, duration and the range of situations in which it occurs. Trait anxiety has similar symptoms as neuroticism and is defined as a long-lasting arousal when a potential future threat appears. (theydiffer.com/difference-between-state-and-trait-anxiety/)

Effectiveness and efficiency of tasks

Effectiveness refers to the quality of task performance indexed by standard behavioral measures (generally, response accuracy). On the contrary, **efficiency** refers to the relationship between the effectiveness of performance and the effort or resources spent in task performance, with efficiency decreasing as more resources are invested to attain a given performance level. (Eysenck et. al, 2007)

Methodology

Brain networks are constructed for each kind of brainwaves. We construct the links of the networks from the imaginary part of coherence (definition). Coherence is a generalization of correlation to the frequency domain (Nunez et al., 1997, 1999). Coherence is usually studied as a relation between EEG or MEG channels while one is interested in relations between brain sites and wants to reduce spurious coherence caused because of algorithm blur (leakage).

Coherency between two EEG-channels is a measure of linear relationship of the two at a specific frequency. Let x_i (f) and x_j (f) be the (complex) Fourier transforms of the time series $\hat{x}_i$(t) and $\hat{x}_j$(t) of channel i and j respectively.

The cross-spectrum is defined as $S_{ij}(f) = \langle x_i(f) x^*{}_j(f) \rangle$ where $*$ stands for complex conjugation and $\langle \quad \rangle$ means expectation value, which practically can be estimated as an average over a sufficiently big number of epochs. Coherency is defined as the normalized cross-spectrum $C_{ij}(f) = \frac{S_{ij}(f)}{S_{ii}(f) S_{jj}(f)^{\frac{1}{2}}}$ and coherence is defined as the absolute value of coherency $Coh_{ij}(f) = |C_{ij}(f)|$. (Nolte et. al, 2004)

Coherence between the i^th and j^th voxels : $C_{i,j}(f) = R\left[C_{i,j}(f)\right] + i\,S\left[C_{i,j}(f)\right]$,

where the real part corresponds to zero-time lag correlation, which can be caused from common interference sources, and the imaginary part which corresponds to non-zero-time lag correlation and can be caused only by true brain interaction. (Kensuke Sekihara, (2009))

The reason why we chose this metric, is due to the fact that this metric by definition cannot be generated as an artefact of volume conduction and is not based on prejudices about the underlying sources, and thus it contains the sources that are truly interacting (G. Nolte et. al, 2004)

Analysis of the resulting network is expected to shed light on the organization of the cortical networks and the interactions that occur in the brain of math-anxious, compared to non math-anxious individuals, as well as on the effect of math anxiety and back tests on some of our network metrics.

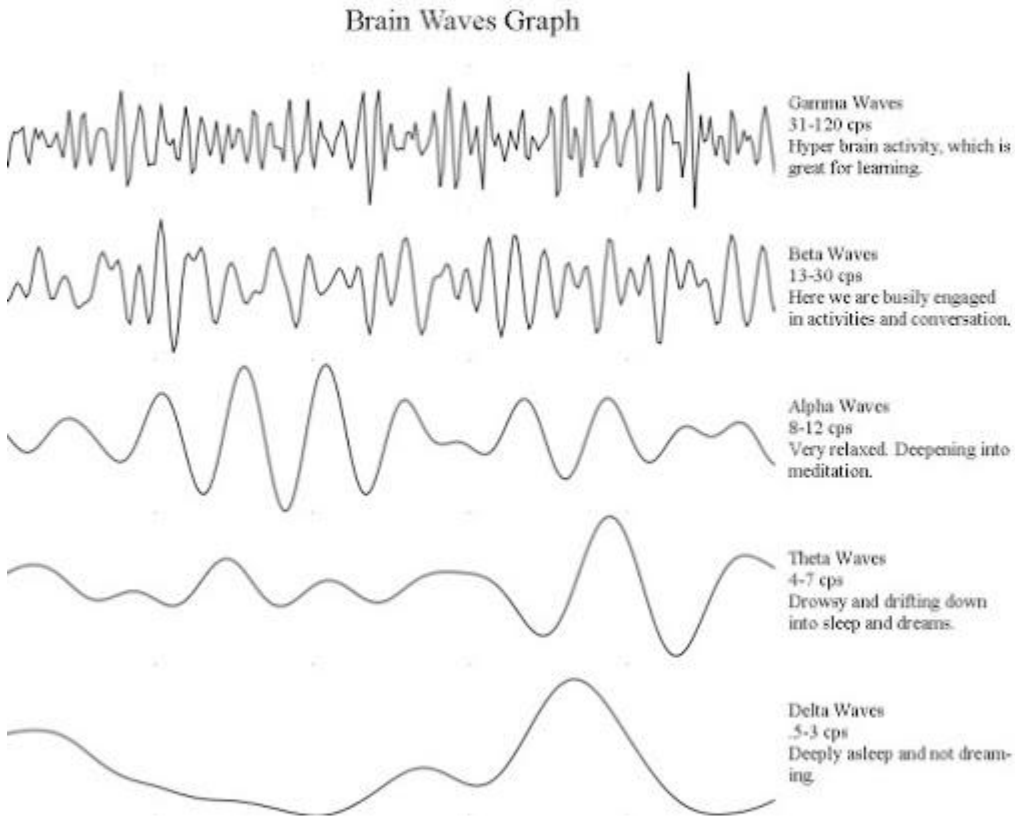
Based on the previous network visualizations, we compute the following basic metrics: degree centrality, betweeness centrality, efficiency (local & global), density, eigenvector centrality, characteristic path length, transitivity, clustering coefficient, and modularity. Statistical tests and a mixed model repeated measures ANOVA were applied on three metrics : density, global efficiency, and local efficiency.

Brainwaves

The brain is an electrochemical organ, consisting of billions of cells, called neurons, communicating with each other. When sets of millions of neurons simultaneously send signals, a huge electrical activity is created in the brain. This kind of activity is defined as a "brainwave"pattern or can be detected using sensitive medical equipment that is able to measure electricity levels over different areas of the scalp. (Berger, H. (1929))

Types of brainwaves

Five main types of brainwaves have been found, ranging from the highest activity to the lowest activity, that represent different frequencies and are activated during different phases of human everyday lives. The following figure illustrates the four main types of brainwaves with short description of some situations they are involved in :



Brainwave patterns and short description for the five main brainwaves.

Source : tbirehabilitation.wordpress.com

The table below briefly summarizes the type of the waves, the frequency of each type(from higher to lower frequencies) and the mental state associated with each type of brainwaves :

Wave	Frequency	Too much	Too little	Optimal	Associated Mental State	How to increase them
Gamma (the least amplitude and fastest frequency	At least 27hz	Anxiety, high arousal, stress	ADHD, depression, learning disabilities	Binding senses, cognition, information processing, learning, perception, REM sleep	Wakefull state. Associated with the formation of ideas, language processing and various types of learning	Meditation
Betta	12hz- 40hz	adrenaline, anxiety, high arousal, inability to relax, stress	ADHD, daydreaming, depression, poor cognition	Conscious focus, memory, problem solving	Wide awake. Mental state most people are during their awaken lives. Associated with emotional stability, energy levels, attentiveness and concentration	Coffee, energy drinks, various stimulants

Alpha	8hz- 12hz	Daydreaming, inability to focus, too relaxed	Anxiety, high stress, insomnia, OCD	Relaxation	Awake but relaxed and not processing much information. Association with ability to recall memories, lessdiscomfort and pain, and reductions in stress and anxiety	Alcohol, marijuana, relaxants, some antidepressan ts
Theta	3hz- 8hz	ADHD, depression, hyperactivity, impulsivity, inattentiveness	Anxiety, poor emotional awareness, stress	Creativity, emotional connection, intuition, relaxation	Light sleep or extreme relaxation. Association with hypnotherapy, as well as self-hypnosis using recorded affirmations and suggestions	Depressants

Delta (greatest amplitude and slowest frequency)	0.2hz-3hz	Brain injuries, learning problems, inability to think, severe ADHD	Inability to rejuvenate body, inability to revitalize the brain, poor sleep	Immune system, natural healing, restorative / deep sleep	Deep, dreamless sleep. Association with self-healing of the body and "resetting" its internal clocks. No dreaming and complete unconsciousness.	Depressants, sleep

Table that briefly summarizes facts about the five main types of brainwaves

Sources : www.scientificamerican.com
www.transparentcorp.com
www.mentalhealthdaily.com

Observing the brainwave patterns of a person, can reveal a lot about brain's functionality (Berger et. al, 1929). For instance, an overabudance of high beta waves shows we have to deal with anxious people, while a great production of slower alpha/theta brainwaves shows people with ADD/ADHD.

Brainwaves not only represent mental states (Berger et. al, 1929), but moreover, when stimulated may alter a person's mental state, something that can be helpful for several mental issues(Wickramasekera et. al,1977).

Generally, people brain is using the beta rhythm by default (Lalo et. al , 2007). When the brain rhythm is diminished to alpha, we are in the perfect condition to acquire new information, maintain facts, process data, execute tasks, learn languages and analyse complex situations. The alpha brain rhythm is, also, characteristic of synthetic thought and creativity, the proper functions of the right hemisphere. Alpha state is, also, connected with activities that give people the sense of calm, as well as meditation and relaxation exercises. The analysis of electroencephalograms of people submitted to tests designed to explore the effect of decreasing the brain rhythm, the attentive relaxation or the deep relaxation, shows significant development of beta-endorphin, noroepinephrine and dopamine, that are associated a sense of mental clarity and formation of memories. Interesting point : the effect may be present for hours, and even days (Lalo et. al, 2007;Zhang, Y; Chen, Y; Bressler, SL; Ding, M, 2008).

Chapter 2

What do we know about math cognition

The foundations of mathematical cognition do not lie in the language faculty.This statement is supported by the fact that there exists an ability to estimate quantities and to reason arithmetically with those estimates in the brains of animals that have no language. In adult humans, there seems to be a non-verbal mechanism for estimating and reasoning about discrete and continuous quantities that acts together with a verbal. The explanation possibly arises far back in the evolution of the brain. As Wigner said: arithmetic reasoning captures deeply important properties of the world, which the animal brain must represent in order to act effectively in it. (Gallistel et. al)

What do we know about math anxiety and education

The 2003 Program for International Student Assessment (PISA) reports that more than 50% of 15-year-old students had feelings of insecurity and emotional stress when they were asked to solve mathematical problems. Similarly, behavioral studies have shown that math anxiety has a negative effect on a wide range of numerical and mathematical tasks, ranging from simple tasks like counting objects to more complex arithmetical problems. The development of math anxiety in students is a result that their teachers are anxious about their mathematical knowledge themselves. According to John Taylor Gatto, Western schools of nowadays are designed in such a way that they promote fear and anxiety, feelings that the teachers experience due to lack of understanding of basic notions such as fractions, algebra, geometry with "proofs", calculus and topology, and that naturally pass to their students.

Students' achievement in school is increased when parents are energetically involved in the procedure . Thus, a simple way for parents to reduce their children's anxiety is to get more involved in their child's education. In addition, anxiety can be reduced, if parents and teachers change their attitude towards the students, as according to Herbert P. Ginsburg from Columbia University, for students matters more the attitude and expectation their teachers and their parents have, than the actual learning. National Council of teachers for mathematics has pointed out the problem and suggests that teachers should accommodate for different learning styles (there are many types of intelligence where teachers need to adapt), create pleasant experiences relevant to math, refrain from tying self-esteem with success to math, allow different approaches to learning mathematics, and emphasize the necessity of innate, quality thinking process rather than steer manipulation of formulas. The following activities are, also suggested for people who experience math anxiety : writing down feeling about math, developing a critical view to observe only the critical information, creating techniques to solve some problems, developing calm and positive ways to face their fear and anxiety for maths, building math confidence gradually. (Hackworth, 1992)

Some scholars point out that math anxiety does not automatically imply failure in math. Ian M. Lyons and Sian L. Beilock (2011) state that not all math anxious individuals perform poorly at math. They conducted research and determined that high math-anxious individuals showed an increased activity in frontoparietal regions simply by anticipating doing math, and that activity accounted for math performance deficits. Moreover, the relation between anticipatory activity in frontoparietal regions and lack of mathematical knowledge of highly math anxious individuals, was fully mediated by activity during math performance in regions such as caudate, nucleus accumbens, and hippocampus, that are necessary for coordinating skills, demands and motivational factors during task execution.

Finally, some scholars have shown that math anxiety and math performance is. also, a matter of culture. For instance, Canadian students show lower success rates than their Korean, Singapore and Indian peers. Researchers have shown that in countries like US, people think that there is a small portion of "gifted" people who are able to understand math, and that hard work is not enough to compensate for the talent. On the contrary, in Japan and Taiwan, parents point on effort more than innate intellectual talent, and additionally, they have greater expectations for school success. Thus they make their children develop a growth mindset, according to which everyone is able to grow their intellectual ability, learn through trial and error and become resilient learners. (Dweck 2006)

What do we know about math anxiety, working memory and behavioral aspects

Studies imply that individuals with a high level of math anxiety have shown an increased error-related brain activity during the processing of a numerical Stroop task, but not when there was no numerical stimuli. Research indicates that the evaluation of errors significantly differ in HMA individuals other then their LMA counterparts. **(**Suárez-Pellicioni et. al, 2013)

Anxiety is merely recognized as a serious problem for learning, as it effects working memory during the learning process, which is so crucial for guiding people's conduct (Baddeley, 1999; Eysenck, 1979) and capability to manage recall (Owens et al., 2008).

Human everyday life consists of active setting of task-relevant and attention shifting to several subgoals. For instance, when an individual is driving, they possibly like talking to other people in the car, while they are simultaneously trying to predict other drivers' behavior, and have a discrete destination in mind. Dominant theories of the field claim that goal-oriented behavior is supported by the system of working memory, which has two basic components : the domain-general central executive and domain discrete storage (Baddeley, 1986; Baddeley and Logie, 1999). The function of the general central executive involves the modulation of the storage subsystems as far as verbal functions (Paulesu et al., 1993; Poldrack et al., 1999) and visuospatial functions are concerned (Courtney et al., 1998; Jonides et al., 1993). According to Smith and Jonides (1999), there are two central executive functions of great importance : attention shifting when managing a dual-task condition, and suspension of the dominant reactions, when there is a cognitive conflict. Through accurate neuroimaging methods, it is indicated that the neural base of the central executive responsible for dual task performance, as well as for Stroop task performance, lies mainly in the anterior cingulate cortex (ACC) and dorsolateral prefrontal cortex (DLPFC) (Bunge et al., 2000; D'Esposito et al., 1995; Smith et al., 2001) (Bush et al., 1998; MacDonald et al., 2000). These two regions, and especially dorsolateral prefrontal cortex, seems to be essential to manage emotional regulation in math anxious individuals (Young et. al, 2012). About the cognitive conflicts, cognitive control has to be risen in math anxious, and more resources need to be used to solve the conflict (Suarez- Pelicconni et. al, 2014). Additionally, math anxiety eliminates attentional and cognitive resources (ACT; Eysenck et al., 2007), therefore, there needs to be more effort for math anxious to reach adequate performance levels. Finally, math anxiety decreases the deactivation of the default mode network, which is generally deactivated during tasks(Pletzer et. al,2015).

It is not only school where a negative association between math anxiety and poor math performance emerges. Research indicates that math anxiety can be proven harmful in various career paths. For instance, nurses with math anxiety avoid math related aspects of their work and tend to calculate wrong drug dosages, while financial controllers seem to have problems with impaired financial planning. Surprisingly, there is an inverse proportion between math anxiety and efficacy : in countries with less proficiency in math, there are more kids experiencing math anxiety (according to PISA).

What do we know about math anxiety and social impact

Denkova et al. (2010) have shown there seems to be a positive correlation between anxiety that is not relevant to task and urges emotions with opposing patterns of activity in affective and controlling brain regions. In addition, there is evidence about the importance of specific median and lateral brain regions of the Prefrontal cortex (PFC) that actually protect against emotional distraction. The results can be helpful to understand changes in neural circuicity underlying emotion-cognition interactions in anxiety disorders like clinical social phobia.

In learning context anxiety can affect the ability of receiving information, processing it, and retrieving it when necessary (Tobias, 1983).

Anxiety has a negative impact on learning and information processing through the effect it has on working memory. Thus, it not only leads to poorer academic performances, school dropout or underachievement, but, also, can cause serious problems in social life, as well as significant problems in school life which are not easily recovered (Bigdeli, 2010)

Additionally, there is a gender stereotype (e.g. math is a masculine sector) that expects women perform worse than men in math. Researchers imply that this is a social effect rather that a biological one. Gender "labeling" is thought to be the reason why women get more math anxious generally and answer math questions in a particular way and not that they are worse than men in math (Dar-Nimrod et. al, 2006). The reason why women react with reduced performance in math owing to prejudices may lie in the work of Lithari et. al (2010). According to Lithari et. al (2010) there is a significant difference in the way genders process emotional stimuli with women showing greater ERP amplitudes owing to unpleasant and high arousing stimuli, and prejudices about math, may cause such a stimuli in women when it comes to math related visions (Lithari et. al, 2010).

Math anxiety : the role of emotional intelligence

Emotional intelligence is the ability to assessing individual's behavior and conduct them in various ways. Emotions have great effect to individuals' skills both in social and private performances. This internal factor influences the way of living ,relation and learning (Lopes et al., 2004)

Emotions can have a great effect on motivating abilities of individuals and improving the process of learning in various fields, especially in students who experience great levels of anxiety. (Carthy et. al, 2009). Unravelling the mysterious effect of anxiety on people emotional intelligence, working memory and learning process is crucial in order to learn to dominate their challenges dedicating their whole working memory and raising their emotional intelligence resources to the learning tasks.

Emotional intelligence is thought to provide a way in order to recognize the real feeling and be able to apply it so as to make accurate decision concerning the learning process. This inner motivator considers moods and reactions in a variety of conditions and makes an attempt to manage them correctly . So, emotional intelligence is defined as an inner motivator that is closely related to the students' abilities and improves the learning and cognitive process. Mayor and Slovey constructed a model to show the role of emotions as inner motivators and explain there are influential emotions on skills and people can change them in various forms(Lopes et al., 2004). Anxiety is thought to spend resources of working memory, and it can affect an individual's ability for learning and interacting. Heimberg et al., (1993) indicates that people who experience high anxiety will be less successful at encoding information and less effective at processing events. The result is justified due to the fact that a great amount of their energy and attention is wasted for managing their anxiety, and so, these people are able to recognize fewer clues from the environment than others, and this leads to losing considerable capacity of their working memory with a negative impact on their learning processing and the interaction with others. Likewise, Goleman (2004) reports that brain activity and one's cognition procedure can be influenced in a negative way by psychological impact of anxiety. Learning as a cognitive process depends on encoding, storing and retrieval procedures. Each of these processes can be molested by anxiety aiming to its negative impact on one’s attention and concentration, as the main behavioral symptom of anxiety is a great difficulty in concentrating (Ansari &Derakshan, 2010; Ansari, Derakshan, & Richards, 2008; Berggren &Derakshan, 2012; Eysenck&Derakshan, 2013).

Aronena et al., (2005) explained that anxiety symptoms negatively affect on concentration and working memory which consequently negatively impact on individual's learning process and performances. Hadwin et al ., (2005) conducted the study to understand anxious individual differences in working memory and found that anxious children experience concentration and that is one of the important factors that makes them spend much more time to complete tasks.

Lapointe (2013) conducted research in order to investigate whether anxiety is linked to one’s distraction, intentional difficulties and limited memory capacity, and resulted to the significant positive correlation between these events but anxiety was specifically related to one’s distractibility. All in all, all of these events can eliminate working memory resources available for overall processing in children, adolescents and adults (Carthy, Horesh, Apter, & Gross, 2010; Eysenck, 1979, 1992) and negatively influence on working memory capacity (Lee, 1999; Visu-Petra, Miclea, Cheie, &Benga, 2009).

Emotions can be an effective inner motivator, as they seem to have strong correlation with positive and negative inner factors like anxiety. Generally, emotions determine a person's skills among individuals. Most of the time, during this process, individuals are motivated for developing their ability in learning field. The presence of anxiety among individuals is assumed as main item in limiting learning, and the negative effect can be decreased with the presence of emotions (Karatas, Alci, & Aydin, 2013; Sajadi, Kiakojouri, & Hatami, 2012).

What do we know about math anxiety and pain :

Lyons and Beilock (2012) have shown that, anticipating an upcoming math-task, can create great discomfort in math anxious individuals and even pain. Especially, the higher the math anxiety, the more the increase of the activity in regions such as bilateral dorso-posterior insula connected with visceral threat detection, and painful experiences. The interesting fact is that this relation was not noticed during math performance, which means math does not hurt itself; however, the anticipation of math can cause pain. These results provide a justification on why high math anxious people tend to avoid math and math-related situations involving math classes or even math-related career paths.

What do we know about math anxiety and buying decisions :

Consumers preferences are the basis for buying decisions. Rather than having well-established preferences, consumers construct new preferences spontaneously, based on a portion of data available at the moment of the creation of the preference (Bettman et. al, 1998). Trying to trace the mechanisms underlying the conformation of buying decisions and the reason why consumers take them, forms a problem of neuroeconomics, the field where neuroscience meets economics (see Appendix I) According to Knutson et. al (2007) excessive prices elevate insular activity and eliminate activity in medial prefrontal regions, a fact that is consistent with the connection between perceived price unfairness and negative effect. These findings confirm the theory of Bechara and Damasio (2005) that our brains map anticipated consequences of purchases from interoceptive emotional signals prior to decision making, which then guide individual's choices. Research implies that math anxiety, promotion format and gender are basic factors that influence buying decisions.
High MA seems to indicate greater reliance on emotional and motivational factors when making buying decisions. Moreover, this category of consumers is trying to do the best to analyze every possible information and incorporate it in their decision to buy or not. It is possible that these effects are provoked owing to a bias for high math anxious females to process the information completely, and so they evaluate offer prices trying to confirm them, and for Low math anxious males to get involved in the dynamics of quantitative reasoning, relative to other males, and so they adopt a decision style that mostly rejects offers. Generally, according to gender selectivity theory, females process more comprehensive, and rely on an amplitude of

information, whereas males adopt a more selecting processing. Speaking about preferences, the feeling about a product is reflected in the decision to buy it or not. For instance, to respond to high prices, consumers often claim they feel price gouged. When the decision of buying is based on rules, it is not probable that strong interoceptive signals should be present to create feelings and then guide behaviour. Mental calculations, are said to create an amount of biomarkers in particular categories of individuals, like muscle tension, elevated cardiac responses, etc. (Berdina et al., 1972). Insula seems to have a key role in evaluating these biomarkers. These responses may be excessive when referring to math anxious consumers. Anterior cingulate, which processes information from anterior insula relevant to the interoceptive state, is possible to be a mediator for the process of engaging extra attentional resources as a gain-control function (Botvinick et al, 2004)

Chapter 3

Brain Connectivity and Network Theory

Brain connectivity is defined as the study and analysis of the brain function using Statistical Analysis and Network Theory to analyze the brain data. Brain connectivity is about studying the connections, however it does not only refer to human brain, but to the brain of several mammals as well, the study of which can give valuable information, tools, and directions for the investigation of the human brain. In this study, the term "brain connectivity" refers to "human brain connectivity". Statistical tools reveal the interdependence between brain regions. By doing so, we obtain the Adjacency matrix that allows us illustrate and study the brain as a mathematical object called a network. Some of such methods are described in detail in the following chapters. Some of the most popular indices that are used to reveal interdependence are Pearson’s Correlation Coefficient, which is useful for the detection of linear correlations and Mutual Information (MI) for nonlinear dependences. The brain regions are assumed as variables, and the researcher just needs to apply the interdependence index to the observational data to get the network.

Functional Connectomics

In Neuroscience, the study of the function of the human brain is referred to as functional connectomics. (Sporns, (2009))The concept is to demonstrate the human brain as a network, the nodes of which can either be brain regions, or specific sensors (e.g in the EEG) that are used to obtain the data, and the edges are the connections that occur between the nodes during a specific task, or during a resting state, when the brain has to practise absolutely nothing. There is a great amount and huge variety of experimental and theoretical studies that make an effort to find patterns and similarities in human brain networks, by obtaining data from people who belong to a particular group given a specific factor (i.e. gender, mental state, age, demographics, math anxiety, task, etc), and then investigate the functional aspects of the results. (Sporns, (2009))

The network perspective used to approach the function of the human brain, is possible due to the proggressive methods for data recording and image acquisition. Moreover, Network theory tools and dynamical systems provide the necessary potential to analyze brain networks, and study their indexes to reach conclusions and even find a diagnosis for medical disorders.

The idea of studying the nervous system as a set of inter-connected neurons is very old in Neuroscience, but the new development of tools and techniques, the greater accuracy in recording and formulating data give a new potential in the field. Scientists develop new non-invasive methods, based on network metrics, in order to find treatment in medical disorders(Bandettini 2012).

The development in the imaging techniques, leads the way for the mapping of the human brain and the interconnected pathways between them, and that is how brain networks are constructed. These networks, which are referred to as the "human Connectome", provide information about the structural features of the brain (structural connectivity) (Sporns et al., 2005; Sporns 2013). There is a research program called "the human Connectome Project" (http://www.neuroscienceblueprint.nih.gov/connectome/), which is designed to investigate the mysteries of the neural networks that are formed in the human brain (connectomes). The collaboration of Neuroscientists with Network Scientists, allows the approach of the brain function from a complex systems' perspective (Sporns 2011). With the progress of more accurate techniques and network tools, the operation to understand the dynamics of complex systems such as the brain is more focused and precise (Newman 2010; Estrada et al., 2012).

The raw data from which brain connectivity is designed, are usually time-series data, which describe patterns of statistical dependence among neurons or other neural elements, and are obtained using techniques, such as electroencephalography (EEG), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI), with several indices of dependence (Rogers et al., 2007).

In addition, the methods mentioned before can be combined in order to achieve greater precision and statistical significance for the results, and better demonstration of functional brain networks. Researchers have attempt to map and model brain networks aiming to understand the relation between functional and structural networks (Sporns 2013).

Moreover, the specific features and differences of the brain networks under various circumstances, provide scientists with biomarkers, that are helpful to identify strange alterations that imply disorders. Sometimes, biomarkers obtained from brain networks, give as clues to understand the differences between healthy and unhealthy brains, and they may even lead the research to find the solution for observed disorders. Such disorders, and even normal aging can cause significant alterations in the connectome. Assessing the connections of the brain network is a field of research with great potential for the correspondence of causality of the disorder.(Horwitz et. al (2011))

Experimental studies involve subjects with neuropsychiatric disorders such as schizophrenia and depression, children with attention-deficit/hyperactivity disorder (ADHD) (Cao et al., 2013; Hong et al., 2014; Bohr et al., 2013), or elderly people with dementia (Di et al., 2012;Frantzidis et. al, 2014). A representative sample size is taken from a population of subjects with the special characteristics and their brain networks are constructed and compared to the brain networks of some healthy individuals, aiming to find significant alterations. Especially, the comparison between functional brain connectivity in people with Alzheimer's or Parkinson's disease and in healthy people and the search for special modifications in the two kinds of brain networks, is very promising, as research indicates that these diseases can even be predicted partially and maybe they can be delayed. (Frantzidis et. al, 2014)The last factor that can cause alterations in the Connectome is normal aging. When people grow old, they suffer problems such as loss of memory, lag in perception and reaction (such as speech or movement), etc. It is very crucial for Neuroscientists to be able to tell the difference between modifications in the brain network due to aging, and alterations due to a brain disease, as the two distinct circumstances must be treated in different ways and meditation(Bamidis et al., 2014; Fischer et al., 2014).

The Connectome

The scientific term "connectome" was firstly introduced by Sporns et. al in 2005 to refer to the "comprehensive map of neural connections in the brain". Scientists attempted to construct networks using elements and connections that form the human brain, and so, a full map of structural characteristics is created. The significance and the interpretation of these structural connections is not restricted to structural connectivity, as there are formed large-scale neuronal dynamics that can be captured as patterns of functional and effective networks of the human brain (Sporns et al., 2005; Friston 2011).

Neuroscientists have proved that some diseases like schizophrenia, multiple sclerosis, and autism provoke abnormal connections in the brain. Furthermore, neuron degenaration, normal aging and Alzheimer's disease, are some other causes of "abnormal brain networks". (Frantzidis et. al, 2014)All the above underline the significance of the Connectome, so that Neuroscientists are able to understand brain growth, abnormality and normal aging (Hong et al., 2014). For the discrete network topology that is shaped in each occasion, scientists suppose that there are some

possible evolutionary factors to be blamed (Sporns 2010).
With the indroduction of the sense of the "Connectome", scientists started to face the brain as a complex, interactive network (Sporns et al., 2005). To be able to construct such a network, it is very important to determine correctly the elements of it (nodes and edges). The nodes and edges are different and depend on the data recording technique and the type of the connections, which can either be structural, functional or effective connections. Usually, the nodes represent brain regions (especially when fMRI is hired as the data acquisition technique) or sensors that are used to record brain activity (especially when the method for the data acquisition is EEG or MEG).

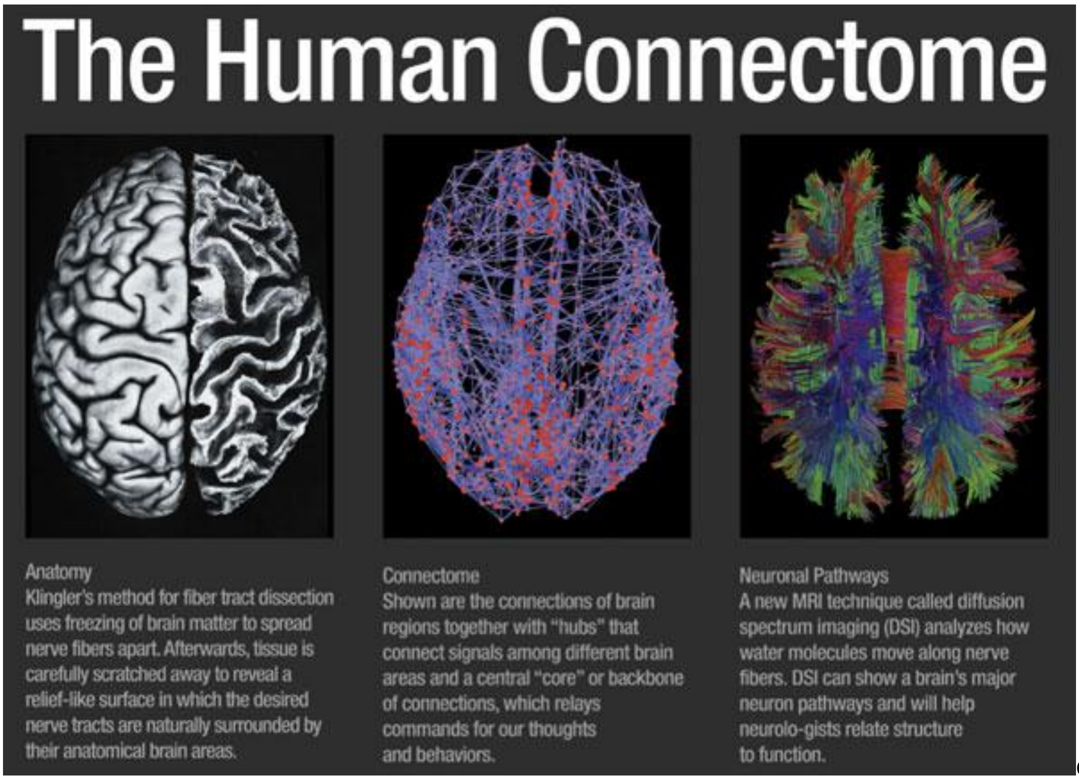


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Fig.1. The human Connectome

Source : https://www.datanami.com/2012/05/01/picking_the_connectome_data_lock/

When the nodes are determined, there are estimated the pairwise dependences between the nodes, according to the metric the researcher wants to use. This way the edges-connections between the nodes are estimated. Structural networks are constructed on the basis of measured fiber tracts or pathways, whereas functional and effective networks are usually formed based on statistical associations estimated from time series data (Sporns 2010). The resulting network is viewed as a graph and its topological and structural properties are assessed using particular tools from Mathematics and Statistics. Statistical analysis of brain networks, allows for localization of pairs of brain regions where "disrupted" connections are encountered. For instance, Korgaonkar (Kargaonkar et al., 2014) observed that patients with depression had abnormal connections in two subnetworks: the first abnormality was localized in regions of the default mode network, and included the rostral anterior cingulate cortex, posterior cingulate cortex, and precuneus, whereas the second one was localized mainly inthe frontal subcortical regions involving the superior and middle frontal cortex, thalamus, and caudate. The regions of these two subnetworks fit very well with the regions where depressive individuals show disruptions.

Types of brain connectivity

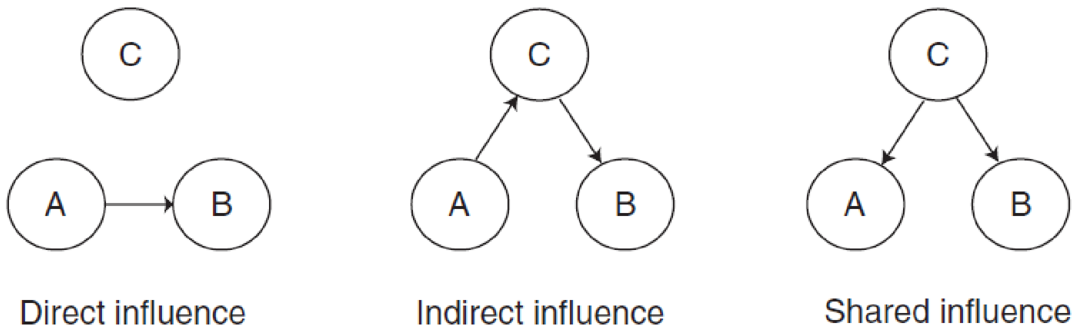
As mentioned before, there are three types of connectivity (structural, functional and effective connectivity), each of which represent different choices of the researcher, in the context of connections in the brain. Brain networks result from anatomical or physiological observations. Regarding the type of the observations, structural or functional networks are formed. The distinction has to be clear when dealing with brain network data sets (Sporns 2013).

According to O. Sporns "brain connectivity refers to a pattern of anatomical links ("anatomical/structural connectivity"), of statistical dependencies ("functional connectivity") or of causal interactions ("effective connectivity") between distinct units within a nervous system". The three types of connectivity are described in more detail as follows:

Structural connectivity is the term used to describe a set of neural elements representing the nodes, that are connected through anatomical links. As far as the human brain is concerned, this kind of connections usually are related to white matter projections (white matter tracts), that connect cortical and subcortical regions (nodes).

O. Sporns mentioned that " structural connectivity is thought to be relatively stable on shorter time scales (seconds to minutes) but may be subject to plastic experience-dependent changes at longer time scales (hours to days)"(Sporns 2013). This is common sense in human neuroimaging studies, and structural brain connectivity is measured as a set of undirected links (as it is difficult to distinguish the direction in the links white matter projections form).

Functional connectivity is indroduced to describe temporal relation between spatially allocated brain regions, regardless if they are connected through physical links or not. It involves the functional connections between nodes (eg, synchronous neuronal oscillations), that possibly do not have any other physical link. These relations can be categorized in three types : direct influence (one node affects another), indirect influence via a third intermediate node, or shared influence (a common third input node affect on two other nodes). All types of relations are demonstrated in the following picture :



Types of interactions between nodes

Fig.2 Source : Poldrack et al., 2011

Functional connectivity is highly time-dependent, as the connections it represents are modulated according to the stimuli from the sensors and the task context, so it can change tens or hundreds of times in milliseconds. Even when measured with techniques that have a very slow sampling rate, such as fMRI, functional connectivity, sometimes exhibit non-stationary fluctuations. Functional connectivity is capable of describing the network behavior underlying cognitive process, and this is the main difference with the structural connectivity, which only represents physical "meaningless" interactions (Sporns 2013).

Functional connectivity can be measured by many neuroimaging or electrophysiological recording methods, and can arise both in situations where the brain is active by default ("at resting state"), and in the context of stimulus- or task-evoked perturbations, as well.

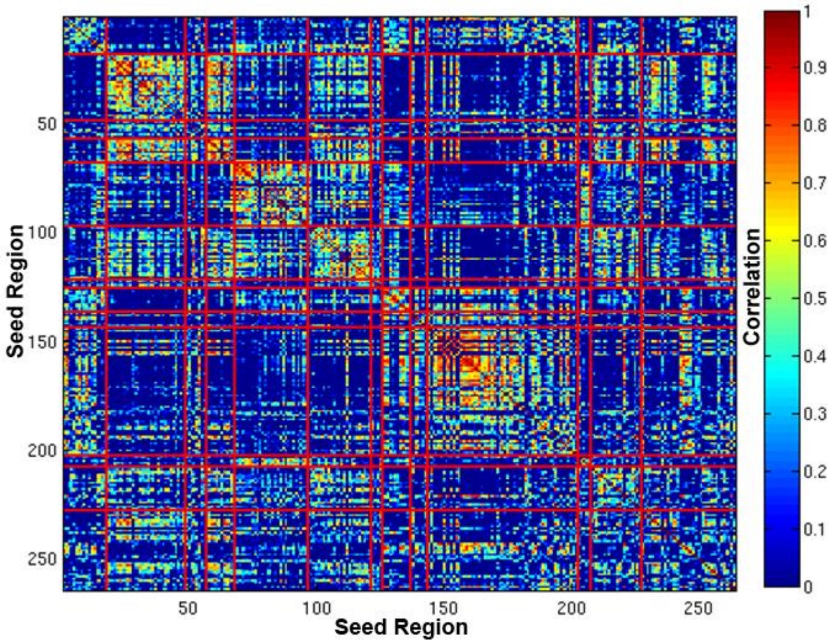


Fig. 3. Matrix showing correlation denoted by color between brain regions.

Source : https://www.neuroscienceblueprint.nih.gov/connectome/

Effective connectivity is used to describe the causality of the directed influences one brain region causes to each other (Rubinov and Sporns, 2010). It is introduced to clarify whether the activity in one brain region causes an influence in another brain region, by providing the ability to test causal models that take into consideration the interactions between brain regions (Poldrack et al., 2011; Friston 2011).

In most of the cases, there is a kind of correlation between the variables. Even though this kind of relation is not surely causal, thus, it is assumed that there is a causal relation, either direct between the two referred variables, or indirect through a third variable which is not measured. Theory of causality is well developed, especially with the discovery of machine-learning techniques that offer mathematically proven methods to test hypotheses on causality, only using observational data. Networks of effective connectivity, are usually constructed as directed graphs, where direction implies the causality. They are, also,called "path diagrams" in the field of path analysis and Structural Equation Modelling (SEM). In these graphs, nodes represent brain areas, while edges represent the causal relations between those areas. The variables that are used in effective connectivity network modelling are restricted (e.g. for fMRI, the variables mostly are the average signal between a set o regions of interest) (Poldrack et al., 2011). Many researchers aim to detect directed causal effects between brain regions, and are trying to construct a model that best explains the empirical data the way effective connectivity implies. This approach is the so-called "network-discovery" (Friston et al., 2011) and includes the finding of graph models for effective connectivity. Despite the promising future for Neuroscience with the study of effective connectivity, researchers avoid using it, and carry out studies based on structural, or functional connectivity instead (Sporns 2013).

Functional Connectivity during task or at rest

One of the basic studies related to functional connectivity is the study of the function of the brain, the collaboration of brain regions and the functional brain network during the performance of a specific task. From such experiments, neuroscientists expect to find connections in the brain network that imply focus,

concentration and willingness in order to accomplish the task.
Another type of measurement is based on the assumption that the brain is "active" all the time and so brainwaves are produced uninterruptedly, even when it seems to be in a resting state and has no task to do. In this type of studies, individuals are having a comfortable seat and are asked to close their eyes or have their eyes open without thinking anything on purpose, during the procedure of the data acquirement. The EEG data obtained in resting state, appeals great interest in the last few years (Luca et al., 2006). There is no activation model during the resting state as there is no task that needs to be completed and brain stays as calm as possible. The methods used for the analysis of data in resting state are : the classical construction of networks from EEG timeseries and, furthermore, the application of tools of graph theory on structural and functional MRI data of human brain.
The behavior of having eyes open (EO) or eyes closed (EC) is not absolutely perceived and conscious in animals (including human individuals). Brain function at EO-EC resting state in the default mode has been recorded in fMRI, however the knowledge about corresponding EEG condition is still restricted, despite the fact that EEG is a common practice in Neuroscience since almost 100 years.
Chen et al. (2007) searched through EEG for the spatial traits of spectral distribution at resting state EO-EC, and for the corresponding relations between the two conditions. They resulted to a network of spectral simultaneous activities, that acted in specific brain regions (EC), and then measured the variation between EO-EC states. They finally demonstrated the usefulness of the EEG default mode network (DMN), as it is the main condition of the human brain. In addition, it is very important for issues concerning the estimation of brain function without tasks involved for the difference between genders, evolutionary alterations due to aging, and response of the brain when it is activated owing to a particular task. DMN is thought to determine the malfunction of a diseased brain at resting state, and assess cognitive variations in human brain.

The Default Mode Network (DMN)

The default mode state is defined as a basic state of the brain when someone is just lying comfortably having their eyes closed (Raichle et al., 2001; Raichle and Synder, 2007). The default mode state determines the default mode network, which is very useful in research as it is proven to be essential to keep a healthy state. The default mode network is basically measured through fMRI (or PET) usually with closed eyes (EC).

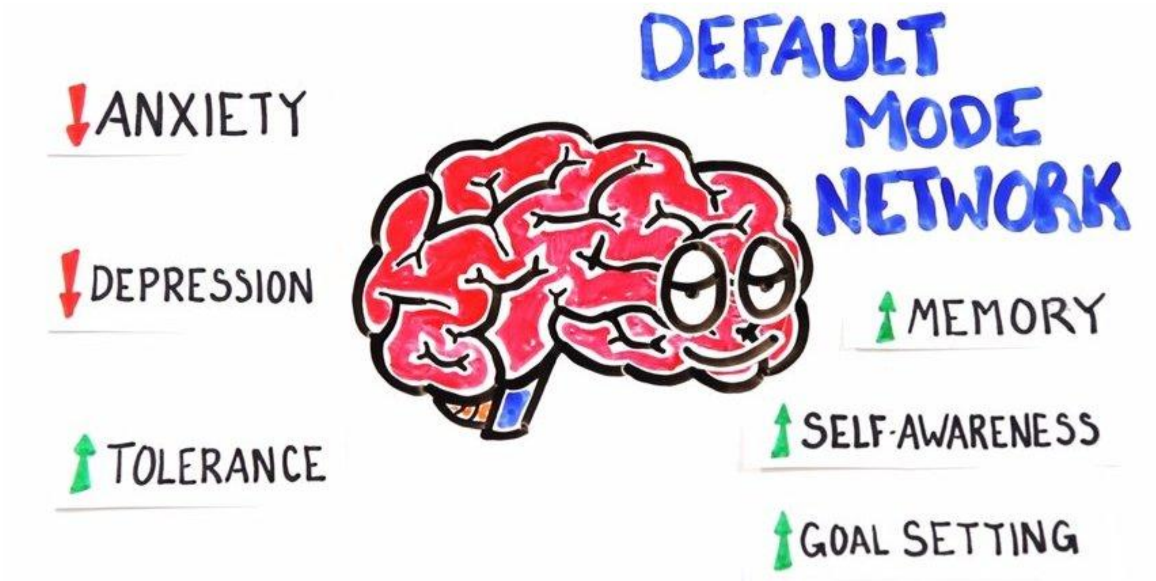


Fig. 4. Characteristics of the Default Mode Network
Source : http://sites.psu.edu/ryanhanchick/2015/09/11/meditation/

Research indicates that the resting state EEG having eyes closed involves a defined set of spectral activities in each region in the classic 7 broad bands (delta, theta, alpha1, alpha2, beta1, beta2, gamma), and so, the EEG default mode network (EEG DMN) is formed. The default mode network is a kind of network which normally has brain regions as nodes, that are active when the individual is at a resting state without any stimulus and is awake having their eyes closed. The default mode network is interconnected and physically defined, and is activated when the subject is preoccupied in internal tasks (demanding activities set as goals) like recalling memories, planning the future, daydreaming, or assessing other's perspectives . The

DMN is also stated as "default network", " default state network" and task-negative network and its trait is the coherent low neuronal oscillations. When the individuals performs a task, the default mode network is deactivated, and task-positive network (TPN) is activated rapidly especially when there are tasks that demand attention sources. With respect to recent findings, it is indicated that TPN is anti-correlated to DMN. The reason lies on the fact that TPN is activated when attention is a necessity, so prefrontal and parietal brain regions are mainly activated, whereas DMN appears when the individual is resting awake and activates the posterior cingulate and medial prefrontal cortex (Hamilton et al., 2011). In the last few decades, neuroscientists study more often DMN, as it is the most popular and it has an easy visualization. The usefulness of the DMN is that gives scientists the opportunity to study neural activity through networks when the individual is at rest. The brain regions involved in DMN, are basically connected in brain retrieval. Thus, the quality and quantity of connections in DMN reflects the kind of brain recovery and provides researchers with information about whether the retrieval is healthy or not. In addition, the DMN connections, regions involved and even brain rhythms are altered due to neurodegenerative disorders, whereas evolutionary diseases can cause inadequate development of the human brain. As a consequence, malfunction or disability is caused in elements participating in the formation of DMN. Practically, the special traits of the resting state of each individual (the connections, the rhythms, activation of the sources) is an index for the health of the brain, and a grade of "healthness".

Concepts and tools from network theory

Network theory has been enormously developed in the 21st century, and is based on graph theory. Network theory provides tools to understand and describe phenomena from very different fields: communication infrastructures, drawing and coloring maps, scheduling tasks, brain structures, social structures, etc. Understanding complex networks requires the right set of tools. In our case, graph theory provides most of the theoretical tools that are used in order to construct, analyze and characterize networks. All real world problems that contain a kind of interaction can be demonstrated and studied as networks. A graph is a geometric structure that illustrates the mathematical binary relations, while a network is the model that represents specific real-world problems. Thus, the network is a graph, which represents real world elements as nodes, and relations between them as edges. However, in Literature, Graph theory and Network theory as well as the concepts of graph and network, are used to imply the same notion.

To construct a graph, a finite set of elements V={$v1$,$v2$,…,vN} is needed, as well as a set of pairs {vi,vj} of the entities of V, defined by $\mathrm{V} \otimes \mathrm{V} = [\mathrm{V}]^2$. Relations on the set of V are represented as a subset $E \subseteq V \otimes V$. A simple graph is a graph without multiple edges or loops, and defined as a pair G=(V,E), where V is a fis inite set of nodes, vertices or points and E is a relation on V, whose elements are known as edges of the graph. The edges are 2-element subsets of V, namely each edge is represented by two vertices of V. Two vertices vi,vj that define an edge of the graph G are called adjacent/ directly connected/neighboring vertices. They are also called endpoints of the edge {vi,vj} (Moyssiadis 2002).

In order to define a network mathematically, we use matrices. The connections between the nodes are represented in the adjacency matrix, and derive from a connectivity method (most of the times a correlation measure is used as a metric). The form of the adjacency matrix is an indicator of whether we have directed or undirected network. The adjacency matrix informs about the number of edges needed to connect each pair of nodes in a graph. In addition, as its name implies, the adjacency matrix is a way to show which of the vertices (or nodes) of a network are adjacent to which other vertices. Given an undirected graph, its adjacency matrix is symmetrical.

The adjacency matrix A of a simple graph is the matrix with elements Aij such that:

A_{ij}={1 $if\ there\ is\ an\ edge\ between\ v_i\ and\ vj$ 0 o$therwise$ }

and as indicated by definition, it is a symmetric, meaning that if there is an edge from vi to vj, there is an edge from vj to vi, too.

In case of weighted networks the edges have some form of weight (or strength), so the adjacency matrix is not cabable of describing the interaction accurately. In this case, the resulting network matrix involves weights instead of presence and absence of an edge, and is referred to as a weighted matrix.

Brain networks are Complex networks. That means they have particular topological features, such as high clustering coefficient, small-worldness, presence of high-degree nodes known as hubs, modularity or hierarchy, that are not typical of random graphs. Most real-world networks are complex systems, so analysis of complex networks forms can be proven to be an important methodological tool. Complex network analysis is a new multidisciplinary approach to the study of complex systems, and aims to characterize brain networks- which, as mentioned before, connect brain regions connected by anatomical tracts or by functional associations-with a number of neurobiologically meaningful and easily computable measures. Modularity is the fraction of the edges within the given groups minus the expected fraction if edges were distributed randomly. The value of the modularity ranges in the interval [−1/2,1). It is positive if the number of edges within groups exceeds the number expected on the basis of chance.

In the current study about ten measures are chosen to characterize the networks constructed from brain data. An individual network measure may characterize several aspects of either global or local brain connectivity, can provide information about functional integration and segregation, quantifies variously importance of individual brain regions, can detect patterns of local anatomical circuitry, and finally tests the resilience of networks to several kinds of attacks or damages (Rubinov, Sporns (2009)).

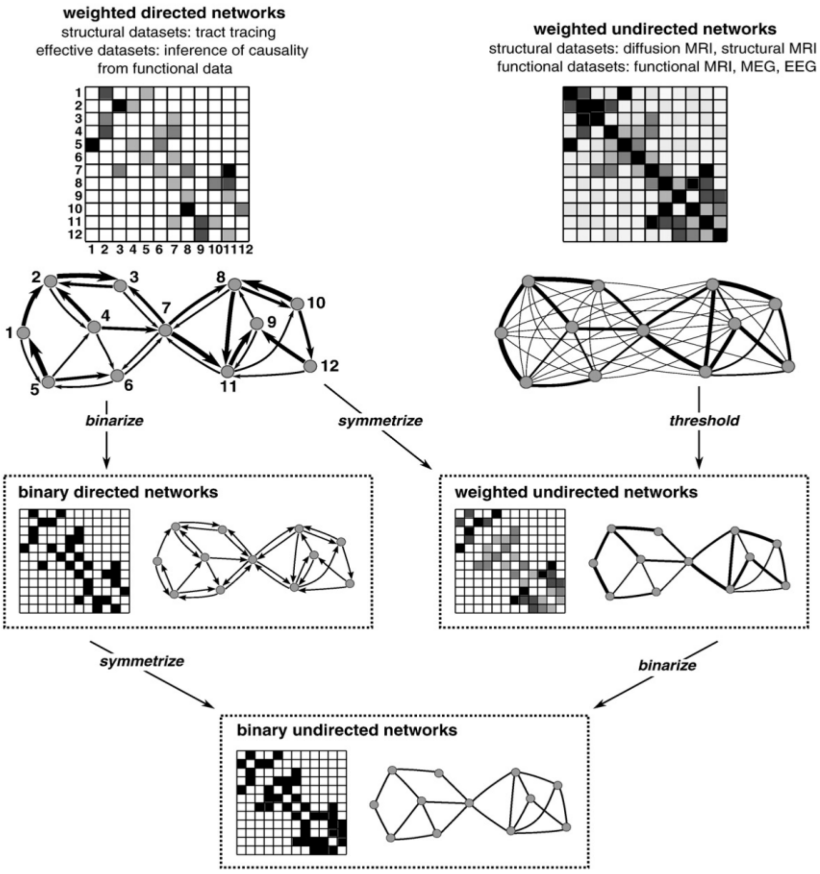


Fig. 5. Construction of brain networks from large scale anatomical and functional connectivity datasets. Networks are generally represented by their connectivity matrices, with rows and columns corresponding to nodes and matrix entries corresponding to links. To simplify the procedure, we transform the networks into a binary undirected form, through thresholding, binarizing, and symmetrizing.

Source : Rubinov, Sporns (2009)

Functional segregation

With the term Functional segregation, we usually refer to the ability of the brain to carry out specialized processing within densely interconnected groups of brain regions. Clusters in anatomical networks, demonstrate the potential for functional segregation in these networks. Additionally, clustering in functional networks indicates an organization of statistical dependencies that imply segregated neural processing. Simple and frequently used measures of segregation are based on the number of triangles in the network, when a high number of triangles is characteristic for segregation. In a local level, the fraction of triangles to triplets around an individual node is defined as clustering coefficient and is the same as the fraction of a node's neighbors that are also neighbors of each other (Watts and Strogatz, 1998). The degree of an individual node is equal to the number of neighbors of the node, which is quantified by the number of links of that node. The mean network degree is defined as the sum of all neighboring weight of the links, is usually used as a measure of density, expressing the total “wiring cost” of the network.

Functional integration

Functional integration of the brain network is the ability for a rapid combination of specialized information from distincted brain regions. Measures of functional integration aim to estimate the fluency of communication between brain regions, and are primarily based on the notion of the path. A path is a sequence of discrete nodes and links. Paths differ proportionally to their lengths, and generally represent statistical relations, or the potential for information flow and functional integration between brain regions, with shorter paths indicating stronger potential. The average distance, i.e. the average shortest path length between all pairs of nodes in the network is defined as the characteristic path length of the network (Watts and Strogatz, 1998) and is the most commonly used measure of functional integration. The average inverse shortest path length is a defined as the global efficiency . Unlike the characteristic path length, the global efficiency may have an interpretation computed on disconnected networks, as paths between disconnected nodes have infinite length, and correspondingly zero efficiency. More generally, the characteristic path length is primarily influenced by long paths (infinitely long paths are an illustrative extreme), while the global efficiency is primarily influenced by short paths. According to the above, it is clear that small-world organization reflects an optimal balance of functional integration and segregation (Sporns and Honey, 2006).

Important brain regions (hubs) often interact with many other regions, accommodate functional integration, and play an important role in network resilience in attacks. Measures of node centrality assess in various ways the importance of individual nodes according to the criteria mentioned above. The degree has a simple and straightforward neurobiological interpretation: nodes with a high degree interact, structurally or functionally, with many other nodes in the network. Betweenness centrality, defined as the fraction of all shortest paths in the network that pass through a given node. Nodes-bridges that connect disconnected parts of the network usually show a high betweenness centrality.

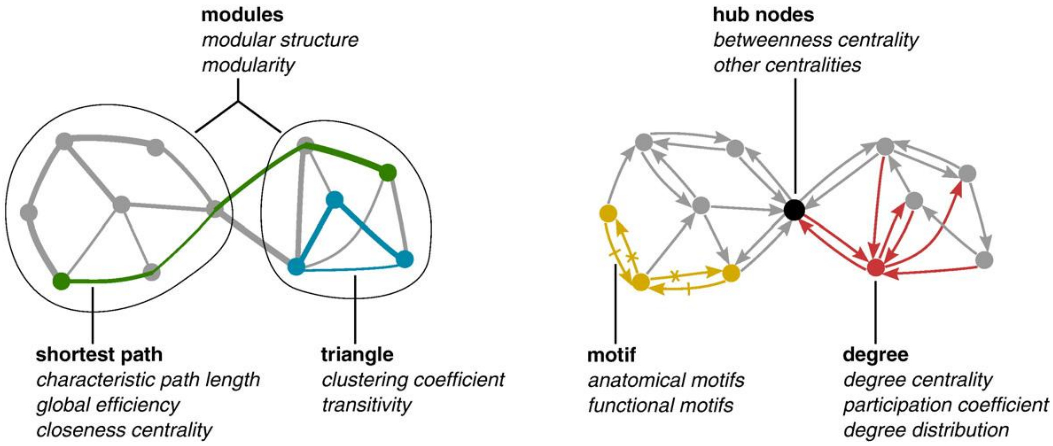


Fig. 6. Basic metrics of the topology of networks. The basic properties of the network where the measures are based, are illustrated in bold. Measures of integration (based on the notion of path length) are demonstrated in green, while measures of segregation (based on triangles) are demonstrated in blue. Measures of centrality are represented in red,and can either be based on deegree of a node, or on shortest paths. Hubs are illustrated in black. Patterns of local connectivity are represented in yellow and are based on motif structure.

Source : Rubinov & Sporns (2009)

In network science, the efficiency of a network is a measure of how efficiently it exchanges information. Efficiency can be applied to both local and global scales in a network, is easier to use than its counterpart path length and can quantify small world behavior in networks as well. Global efficiency is a measure that quantifies the exchange of information across the whole network where information is simultaneously exchanged. Local efficiency measures the network's resistance to failure on a small scale. This means that local efficiency of a node is typical of how well information is exchanged by its neighbors when the node itself is removed.

Efficiency is, also, used to unravel cost-effective structures in weighted and unweighted and determine how economically a network is constructed. Efficiency is a very important measure in neuroscience studies for the quantification of information transfer across neural networks, where the physical space and resource constraints are limited.

Chapter 4

Methodology of research

Data

Data were obtained from university students during the processing of solving four types of arithmetic problems (one and two-digit addition and multiplication) and a working memory task comprised of three levels of difficulty (1,2,and 3-back test). The nodes of our resulting network will be sensors that are used to record brain activity. Once the nodes are determined, there are estimated the pairwise dependences between the nodes, according to imaginary part of coherence. Thus, a matrix is extracted that contains the weights of the links.

We have 576 matrices with dimension 52x52 (each of the 52 nodes corresponds to an electrode). We aim to analyze the netwrorks through Matlab to reach conclusions about some characteristics and the structure of the networks, and then analyze some network metrics (density, global efficiency, local efficiency) through SPSS, to declare whether math anxiety and difficulty in Back tests influence these metrics.

Processing with Matlab

Our data consists of 576 datasets of 52x52 matrices, which are constructed based on a metric called Imaginary Part of Coherence. These matrices, contain the weights of the links between each pair of nodes. Nodes stand for electrodes and links stand for a kind of correlation between them.
For the primer analysis of the networks, we choose to employ Matlab 2015b and the toolboxes : Brain Connectivity toolbox and Statistics, Machine Learning Toolbox, and Information Theory Toolbox.
The procedure in Matlab is the following :

1) Loading of a dataset

2) Creation of variables (each column is a variable)

3) Application of the following script on the variables created

```
A = [VarName1 VarName2 VarName3 VarName4 VarName5 VarName6 VarName7
VarName8 VarName9 VarName10 VarName11 VarName12 VarName13 VarName14
VarName15 VarName16 VarName17 VarName18 VarName19 VarName20
VarName21 VarName22 VarName23 VarName24 VarName25 VarName26
VarName27 VarName28 VarName29 VarName30 VarName31 VarName32
VarName33 VarName34 VarName35 VarName36 VarName37 VarName38
VarName39 VarName40 VarName41 VarName42 VarName43 VarName44
VarName45 VarName46 VarName47 VarName48 VarName49 VarName50
VarName51 VarName52]

n = 52;

A = randn(n);

A(1:n+1:n*n) = 0;

A(A<0)=0;
```

This script is used in order to set negative values of the matrix to zero, and therefore work only with the positive ones. The reason why we do this, is because we are only interested in positive interactions between nodes-electrodes, that means we are interested in simultaneous activation of the regions represented by electrodes. The negative number indigates negative interaction, that means a region is activated when another is deactivated. It would make sense to analyze the same network with both positive and negative weights, however we are not interested in it in the current study. On the contrast, using the absolute value of the matrix would be of no meaning, as this would give us negative values as positive,that is, regions that are activated when others are deactivated, are represented as regions which are activated simultaneously.

4)Computation of the following measures : diameter, eccentricity, degree centrality, betweenness centrality, eigenvector centrality, edge betweenness, nodal strength, characteristic path length, clustering coefficient, transitivity, global ad local efficiency, density, modularity, entropies of the various centrality measures.

The procedure above is followed for all 576 datasets of interest. By the end of the procedure we save our results in a database(e.g access)

Analysis of the results from Matlab

After the processing with matlab, we analyze the results to reach a conclusion: all our 576 networks constructed from our datasets have small world properties .That is they have a higher clustering and almost the same average path length than the random networks with the same number of nodes and edges. Small world properties are typical of cortical maps or brain networks. Additionally, these networks do have a high global, as well as high local efficiency for almost all their nodes (basic characteristic of small world networks). Furthermore, these networks, are have a relatively high modularity (groups of nodes that are more densely connected together than to the rest of the network) as expected from their small-world structure. About the centrality measures, nodes-electrodes 9 and 19 seem to have the higher betweenness centrality than others especially in women, whereas nodes 35 and 28 seem to be the ones with the highest betweenness centrality in men. Proportionally, the node with the highest degree centrality in most of the cases seem to be electrode 50. Further analysis of other measures that are computed, are out of the purposes of this work. However, once the the measures are already computed, their analysis would be a great work for future research.

Comparison between Mixed ANOVA and two-way repeated measures ANOVA

Before we test the influence of Math anxiety and Back tests on our metrics, we need to determine which statistical tool we are going to use. We compare Mixed ANOVA and two-way repeated measures ANOVA and then we state which one we choose and why.

Both the mixed ANOVA and two-way repeated measures ANOVA involve two factors, as well as the same purpose that is to clarify whether there is an interaction between these two factors on the dependent variable. However, the fundamental difference is that in the case of two-way repeated measures ANOVA we have two "within-subjects" factors, while in a mixed ANOVA we only have one "within-subjects" factor and a "between-subjects" factor. As a result, in a two-way repeated measures ANOVA, all subjects undergo all conditions. In addition, unlike the mixed ANOVA, subjects are not separated into different groups based on some "between-subjects" factor (e.g., a characteristic such as gender, or math anxiety. Considering the above we pick out Mixed 2x3 ANOVA design.

Mixed 2x3 ANOVA

We employ mixed 2x3 ANOVA when one of the variables takes the form of repeated measures and the other one is between subjects, which means there is a partition where independent groups of participants can be identified. In our case, there are two independent groups of participants, for each of which three repeated measures are taken.

A mixed ANOVA compares the mean differences between groups that have been split on two "factors" (also known as independent variables), where one factor is a "within-subjects" factor and the other factor is a "between-subjects" factor. In our case, Math anxiety is the Between subject factor, because math anxiety defines a partition "between" the population, and Back-test as the within subjects variable (expresses repeated measurement "within" the population).

The primary purpose of a mixed ANOVA is to make clear if there is an interaction between your within-subjects factor and between-subjects factor on the dependent variable. Once you have established whether there is a statistically significant interaction, there are a number of different approaches to following up the result. Mixed ANOVA is an omnibus test statistic and is not able to inform us about which specific groups within each factor were significantly different from each other. (Laerd statistics : statistics.laerd.com)

Assumptions for the mixed design ANOVA

Before analyzing our data using Mixed 2x3 ANOVA, we need to make sure that our data can actually be analyzed this way. We can check the power of the method through the validation of some basic assumptions.

Assumption #1: The **dependent variable** should be continuous (i.e., they are either **interval** or **ratio** variables). Examples of **continuous variables** include time (measured in hours), intelligence (measured using IQ score), exam performance (measured from 0 to 100), weight (measured in kg), and so forth.

Assumption #2: The **within-subjects factor** should consist of **at least two categorical**, **"related groups"** or **"matched pairs"**. "Related groups" indicates that the same subjects are present in both groups. The reason that it is possible to have the same subjects in each group is because each subject has been measured on two occasions on the same dependent variable, whether this is at two different "time points" or having undergone two different "conditions". In our case the same subjects have undergone three different conditions (3 Back tests).

Assumption #3: The **between-subjects factor** should consist of **at least two categorical**, **"independent groups"**. Independent variables that meet this criterion include gender (2 groups: male or female), math anxiety (2 groups : Math anxious or Non math anxious individuals), etc.

Assumption #4: There should be **no significant outliers** in **any group** of our **within-subjects factor** or **between-subjects factor**. Outliers are single data points within the data that do not follow the usual distribution as the others. These data points may have a negative effect on the mixed ANOVA, **distorting the differences between the related groups (whether increasing or decreasing the scores on the dependent variable)**, which reduces the accuracy of the results.

Assumption #5: The **dependent variable** should be **approximately normally distributed for each combination of the groups of the two factors** (within-subjects factor and between-subjects factor). Also, when we talk about the mixed ANOVA, we require approximately normal data, because it is quite "robust" to violations of normality, meaning that assumption can be a little violated and still provide valid results. Shapiro-Wilk test of normality (for 'actual data') and Kolmogorov-Smirnov test of normality are used to assess "how normally" are the data distributed.

Assumption #6: There needs to be **homogeneity of variances for each combination of the groups of two factors** (within-subjects factor and between-subjects factor). We tested this assumption with Levene's test for homogeneity of variances.

Assumption #7: Assumption of **sphericity should not be violated**, meaning that the **variances of the differences between the related groups of the within-subject factor for all groups of the between-subjects factor must be equal**. Sphericity is checked by Mauchy's test of Sphericity. In case the assumption is not met, there is an automated correction, and the statistical tool is Greenhouse-Geisser or Huynh-Feldt. (Laerd statistics : statistics.laerd.com)

Processing with SPSS

After the analysis with matlab, we have analyzed some particular global measures in SPSS. Especially, we took each value of density and global efficiency, for every group of individuals (math anxious- non math anxious, men-women) and for every brain rhythm. We put all these values into excel files and transformed the data in such a manner to fit in a 2x3 ANOVA design.

We check if the assumptions mentioned above are met, using the appropriate tests. After that, we ran a 2x3 ANOVA for each measure (global efficiency, density) and each brain rhythm in order to make it clear whether there is an interaction between our within-subjects factor (Backtest) and between-subjects factor (Math anxiety) on the dependent variable (global efficiency, density).

Additionally, we have analyzed a local measure : local efficiency. We took each value of local efficiency for every group of individuals, for every brain rhythm, and for every electrode in the brain rhythm. That gives as a total of 52x6x48 = 14976 values of local efficiency.

We put all these values into excel files and transformed the data in a way to fit in a 2x3 ANOVA. We compute average local efficiency, that means the mean value of all 52 electrodes for each person, each brain rhythm and each number of backtest . "globalize" the local measure of efficiency. After that, we ran a 2x3 ANOVA for each brain rhythm in order to clarify if there is a statistically significant interaction between our within-subjects factor (Backtest) and between-subjects factor (Math anxiety) on the dependent variable (local efficiency).

Chapter 5

Statistically significant results :

We only list and comment the results that are statistically significant. Overall results from SPSS analysis are listed in Appendix B.

We found non statistically significant influences of math anxiety and difficulty in Back tests on global efficiency and density. We only have statistically significant results for average local efficiency.

Alpha1 :

Descriptive Statistics

	MATH ANXIETY	Mean	Std. Deviation	N
BT1	Math anxious MA	,678847130490815	,016957242089620	16
	Non math anxious NMA	,686959934221036	,026845706346097	16
	Total	,682903532355925	,022712106524709	32
BT2	Math anxious MA	,680355200026533	,012289330585679	16
	Non math anxious NMA	,684979399983397	,023792189495984	16
	Total	,682667300004965	,018985905898331	32
BT3	Math anxious MA	,678967026750371	,014030216193602	16
	Non math anxious NMA	,675188904021393	,022099152857289	16
	Total	,677077965385882	,018517198825447	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,002	2	,001	3,013	,051
	Greenhouse-Geisser	,002	1,966	,001	3,013	,052
	Huynh-Feldt	,002	2,000	,001	3,013	,051
	Lower-bound	,002	1,000	,002	3,013	,086
BT * MATHANXIETY	Sphericity Assumed	,002	2	,001	2,588	,078
	Greenhouse-Geisser	,002	1,966	,001	2,588	,079
	Huynh-Feldt	,002	2,000	,001	2,588	,078
	Lower-bound	,002	1,000	,002	2,588	,111
Error(BT)	Sphericity Assumed	,077	204	,000		
	Greenhouse-Geisser	,077	200,495	,000		
	Huynh-Feldt	,077	204,000	,000		
	Lower-bound	,077	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204)= 3,013 is marginally significant at 0,051, almost 0,05. This means that ignoring whether participants are math anxious or non math anxious, there is an overall marginally significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,002	1	,002	4,258	,042
	Quadratic	,000	1	,000	1,477	,227
BT * MATHANXIETY	Linear	,002	1	,002	4,435	,038
	Quadratic	,000	1	,000	,311	,578
Error(BT)	Linear	,042	102	,000		
	Quadratic	,034	102	,000		

From the above table it is clear that we have a statistically significant linear component for Back test, so we can deduce that average local efficiency is changing linearly as Back tests are getting more difficult.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	144,644	1	144,644	318156,457	,000
MATHANXIETY	,001	1	,001	1,530	,219
Error	,046	102	,000		

We have a non significant effect for math anxiety.

Pairwise Comparisons

Measure: Average local efficiency

(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1	2	,000	,003	1,000	-,006	,007
	3	,006	,003	,125	-,001	,013
2	1	,000	,003	1,000	-,007	,006
	3	,006	,003	,086	-,001	,012
3	1	-,006	,003	,125	-,013	,001
	2	-,006	,003	,086	-,012	,001

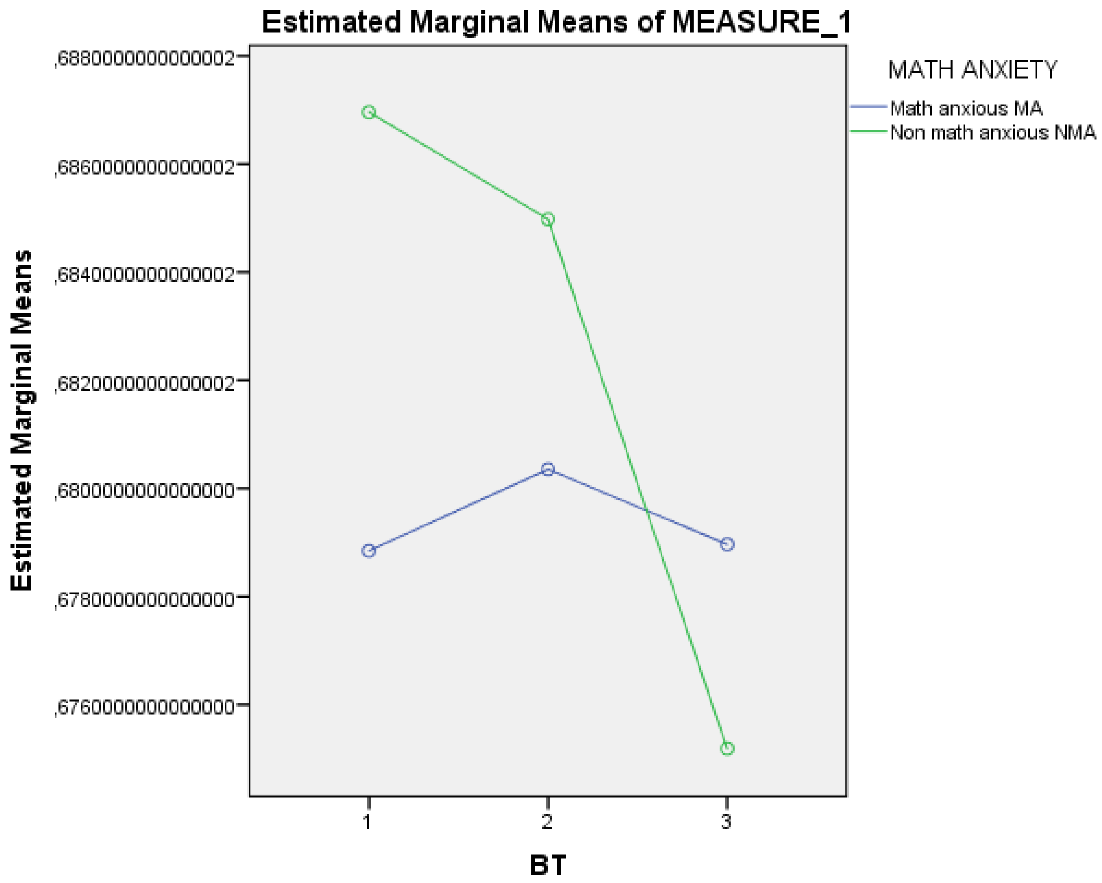
Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

The Bonferroni pairwise comparisons in the table above are equal to independent t-tests. Speciffically, if you divide the Mean Difference by the Standard Error of the Difference, you will get exactly the *t* values you would have if you ran a t-test for the mean of each pair.

We can see that we do not have a statistically significant result in our pairwise comparisons.

From the graph below, we can deduce that the network of non math anxious individuals has greater average local efficiency for the alpha rhythm for the first and the second back tests, than math anxious ones, when in the third back test math anxious individuals out-performed non math anxious ones as far as local efficiency is concerned. The within subject test indicate that there is a significant **Back test** effect, whereas the interaction does not reach a convenient level of significance. The variable group is not significant as indicated from the between subjects contrasts, and that is the reason why the two lines are not very far.



Alpha 2 :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,677313362024278	,016576299101397	16
	Non math anxious	,692727435906417	,023667343264934	16
	Total	,685020398965348	,021757309629832	32
BT2	Math anxious	,689330157759213	,012973726614958	16
	Non math anxious	,694141713609022	,025415046446375	16
	Total	,691735935684118	,020224055269209	32
BT3	Math anxious	,677847849447941	,017217673096823	16
	Non math anxious	,683582952297254	,019797925547881	16
	Total	,680715400872597	,018685929701740	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,006	2	,003	9,759	,000
	Greenhouse-Geisser	,006	1,964	,003	9,759	,000
	Huynh-Feldt	,006	2,000	,003	9,759	,000
	Lower-bound	,006	1,000	,006	9,759	,002
BT * Mathanxiety	Sphericity Assumed	,002	2	,001	2,728	,068
	Greenhouse-Geisser	,002	1,964	,001	2,728	,069
	Huynh-Feldt	,002	2,000	,001	2,728	,068
	Lower-bound	,002	1,000	,002	2,728	,102
Error(BT)	Sphericity Assumed	,067	204	,000		
	Greenhouse-Geisser	,067	200,313	,000		
	Huynh-Feldt	,067	204,000	,000		
	Lower-bound	,067	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204)= 9,759 is significant at 0,000. This means that ignoring whether participants are math anxious or non math anxious, there is an overall significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,001	1	,001	2,759	,100
	Quadratic	,005	1	,005	17,695	,000
BT * Mathanxiety	Linear	,001	1	,001	3,486	,065
	Quadratic	,001	1	,001	1,868	,175
Error(BT)	Linear	,036	102	,000		
	Quadratic	,031	102	,000		

From the above table it is clear that we have a statistically significant quadratic component for Back test, meaning that mean average local efficiency is increasing/decreasing and then decreasing/increasing in the final measurement.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	146,751	1	146,751	287010,714	,000
Mathanxiety	,006	1	,006	11,424	,001
Error	,052	102	,001		

The table above, demonstrates that the effect for the "group" (effect of math anxiety) is significant.

airwise Comparisons

Measure: Average local efficiency

(I) Math anxiety	(J) Math anxiety	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Math anxious	Non math anxious	-,009*	,003	,001	-,014	-,004
Non math anxious	Math anxious	,009*	,003	,001	,004	,014

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.

The Bonferroni pairwise comparisons in the table above are equal to independent t-tests. We can see that there is a statistically significant difference between Math anxious and non math anxious individuals.

Pairwise Comparisons

Measure: Average local efficiency

(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-,007*	,002	,015	-,012	-,001
	3	,004	,003	,299	-,002	,011
2	1	,007*	,002	,015	,001	,012
	3	,011*	,003	,000	,005	,017
3	1	-,004	,003	,299	-,011	,002
	2	-,011*	,003	,000	-,017	-,005

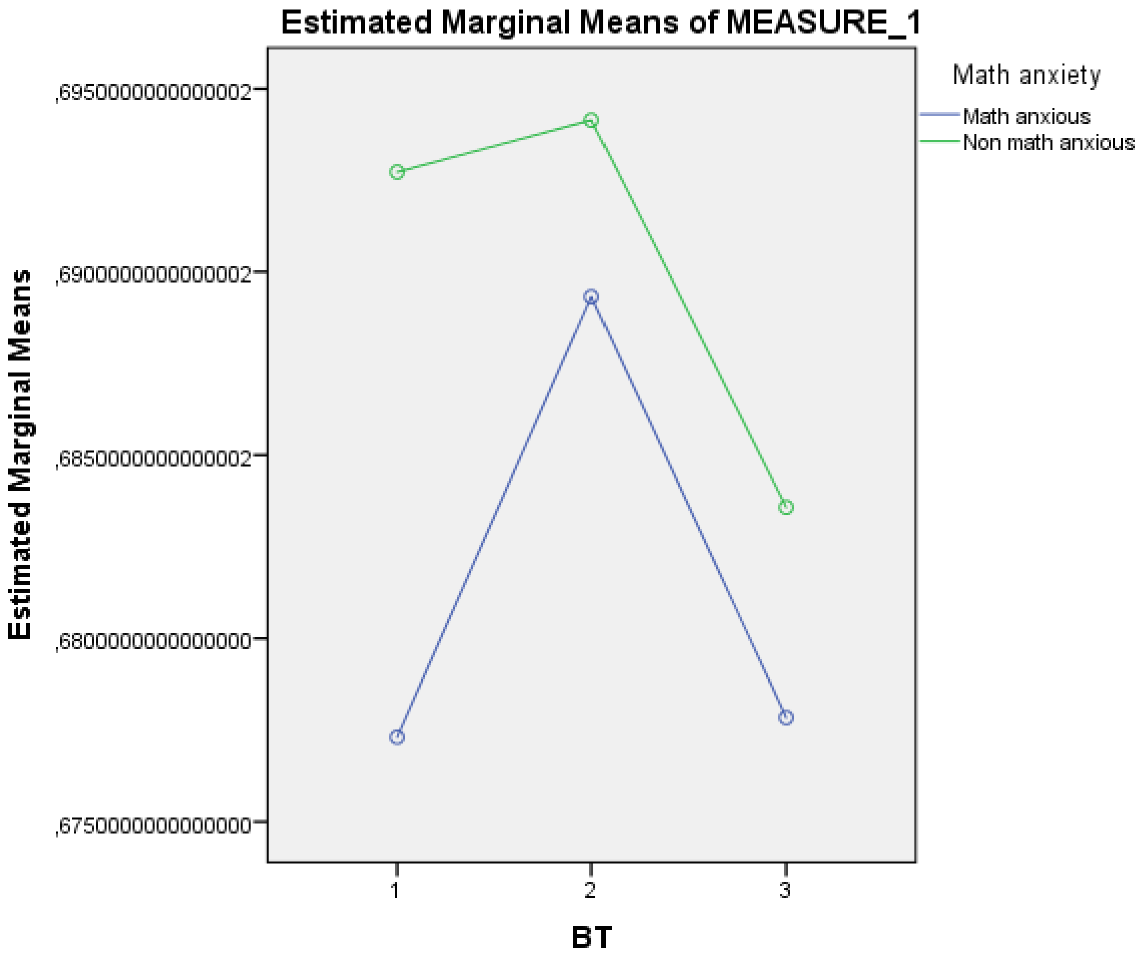
Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.

From the table above, which is designed based on Bonferroni intervals, we can deduce that the differences appear between pairs Back test 1 - Back test 2 and Back test 2 - Back test 3.

The between groups test indicates that there the variable **group (math anxiety)** is significant, consequently in the graph we see that the lines for the two groups are rather far apart. The within subject test indicate that there is a significant **back test** effect, in other words, the average local efficiency does change over the back tests, both groups are getting more efficient locally on average from BT1 to BT2, and less efficient from BT2 to BT3. Moreover, the interaction of **Back test** and **group** is not significant which means that the groups are changing over Back tests in a same way, which means that in the graph the lines will almost be parallel.



Betta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,676133138811009	,019100792315265	16
	non math anxious	,683608362786206	,023660443523176	16
	Total	,679870750798608	,021724299156238	32
BT2	math anxious	,687899308563927	,015795667055813	16
	non math anxious	,674342590698899	,020037618744719	16
	Total	,681120949631413	,019202516010970	132
BT3	math anxious	,680354397862655	,016383179519660	16
	non math anxious	,679641536556711	,023091925666300	16
	Total	,679997967209683	,019926354252743	32

Sphericity is not violated, so we take the values for sphericity assumed (first row without corrections). In the table below, we can see that F (2, 204)= 7,518 is significant at 0,001. This means that there is a significant interaction between the two independent variables: target group (math anxiety) and Back test.

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	9,846E-5	2	4,923E-5	,127	,881
	Greenhouse-Geisser	9,846E-5	1,986	4,958E-5	,127	,880
	Huynh-Feldt	9,846E-5	2,000	4,923E-5	,127	,881
	Lower-bound	9,846E-5	1,000	9,846E-5	,127	,723
BT * Mathanxiety	Sphericity Assumed	,006	2	,003	7,518	,001
	Greenhouse-Geisser	,006	1,986	,003	7,518	,001
	Huynh-Feldt	,006	2,000	,003	7,518	,001
	Lower-bound	,006	1,000	,006	7,518	,007
Error(BT)	Sphericity Assumed	,079	204	,000		
	Greenhouse-Geisser	,079	202,579	,000		
	Huynh-Feldt	,079	204,000	,000		
	Lower-bound	,079	102,000	,001		

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	8,416E-7	1	8,416E-7	,002	,964
	Quadratic	9,762E-5	1	9,762E-5	,273	,602
BT * Mathanxiety	Linear	,001	1	,001	2,075	,153
	Quadratic	,005	1	,005	13,914	,000
Error(BT)	Linear	,043	102	,000		
	Quadratic	,036	102	,000		

We can see that the quadratic component of the interaction is statistically significant, reflecting the fact that the increase levels off, and falls, at the last measurement(or the decrease falls and levels off in the last measurement)

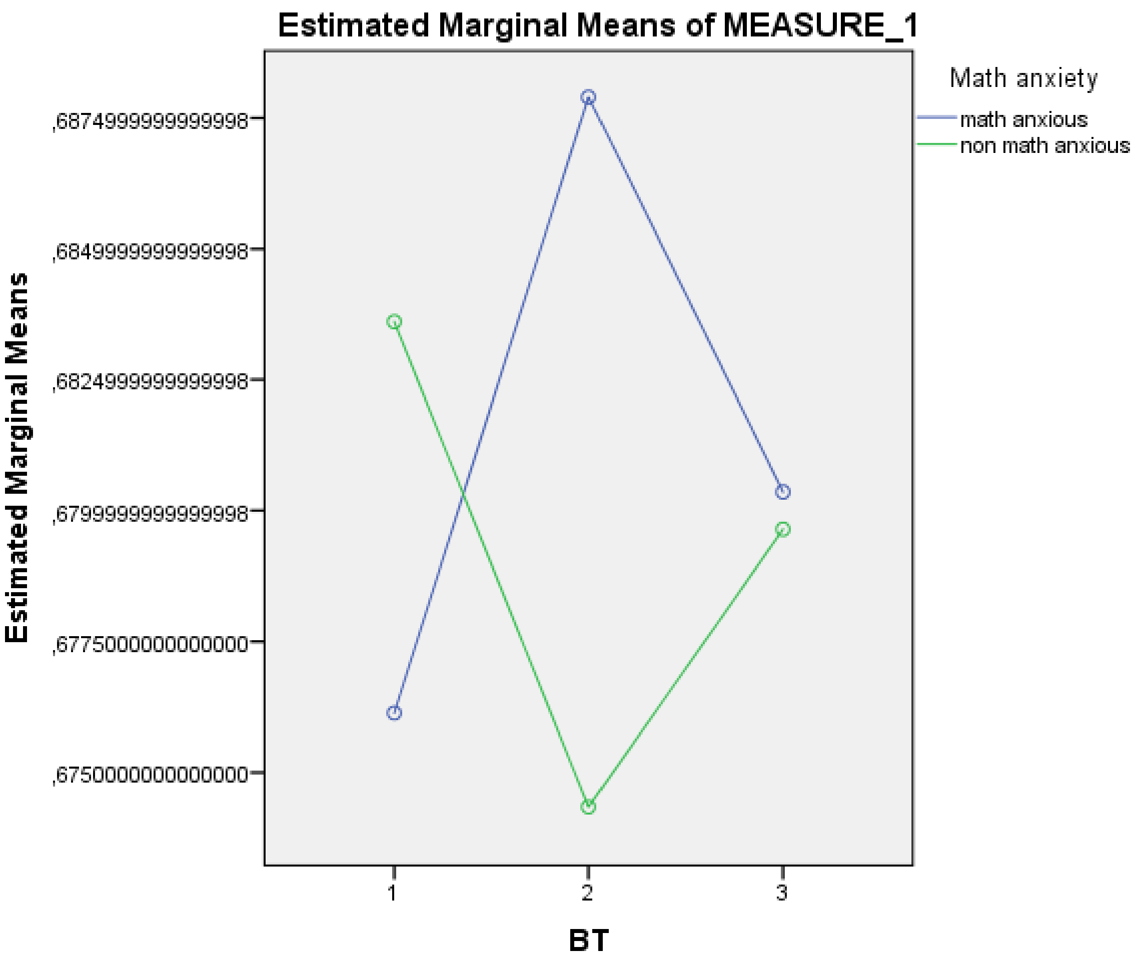
Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	144,409	1	144,409	351155,635	,000
Mathanxiety	,000	1	,000	,973	,326
Error	,042	102	,000		

The effect of the group (math anxiety) is not statistically significant according to the table above.



The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups intersect. The within subject test indicate that there is not a significant **back test** effect. Moreover, the interaction of **back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel. In the graph we see that the groups have non-parallel lines and they have a great gap as far as Back test 2 is concerned, as implied from the quadratic component of the interaction.

Delta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,677298716885079	,013638915711303	16
	Non math anxious	,673248222354743	,023912672881491	16
	Total	,675273469619911	,019477695086627	32
BT2	Math anxious	,684858256681881	,016235869791716	16
	Non math anxious	,674187832611482	,023280484299577	16
	Total	,679523044646682	,020679033978872	32
BT3	Math anxious	,682763718219719	,015556775589770	16
	Non math anxious	,678436258623113	,025394297710447	16
	Total	,680599988421416	,021068073748442	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,002	2	,001	2,268	,106
	Greenhouse-Geisser	,002	1,966	,001	2,268	,107
	Huynh-Feldt	,002	2,000	,001	2,268	,106
	Lower-bound	,002	1,000	,002	2,268	,135
BT * Mathanxiety	Sphericity Assumed	,001	2	,000	1,002	,369
	Greenhouse-Geisser	,001	1,966	,000	1,002	,368
	Huynh-Feldt	,001	2,000	,000	1,002	,369
	Lower-bound	,001	1,000	,001	1,002	,319
Error(BT)	Sphericity Assumed	,074	204	,000		
	Greenhouse-Geisser	,074	200,563	,000		
	Huynh-Feldt	,074	204,000	,000		
	Lower-bound	,074	102,000	,001		

None of the above tests is statistically significant to influence the average local efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	143,618	1	143,618	288637,826	,000
Mathanxiety	,003	1	,003	6,320	,014
Error	,051	102	,000		

The effect of the group (math anxiety) is statistically significant with $F(1, 102)=6{,}320$ being significant at $p = 0{,}014$.

Pairwise Comparisons

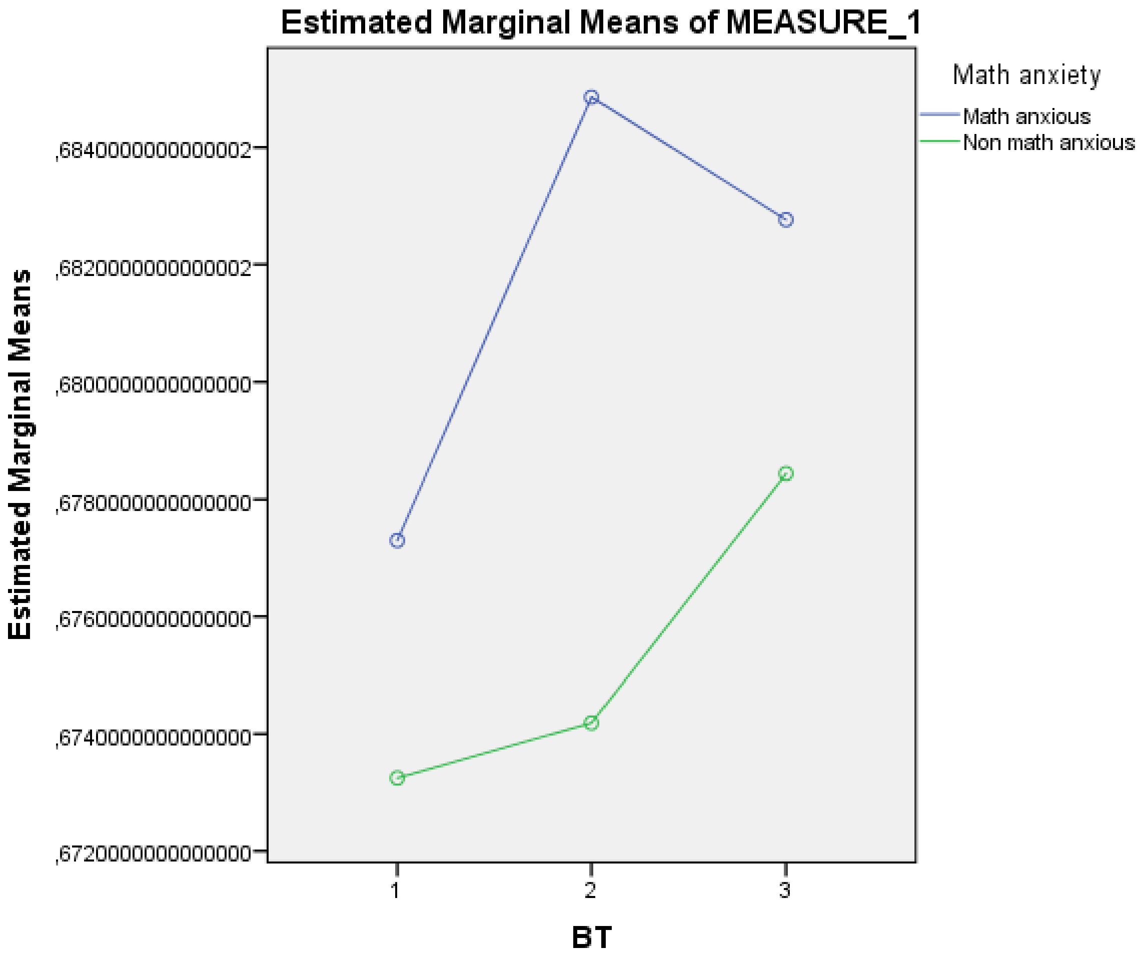
Measure: Average local efficiency

(I) Math anxiety	(J) Math anxiety	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
Math anxious	Non math anxious	,006*	,003	,014	,001	,011
Non math anxious	Math anxious	-,006*	,003	,014	-,011	-,001

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.



The between groups test indicates that the variable **group (math anxiety)** is significant, consequently in the graph we see that the lines for the two groups are rather far apart. The within subject test indicates that there is not a significant **back test** effect, in other words, the mean average local efficiency does not change significantly locally in efficiency over Back tests. In addition, since the lines do not intersect, we are not surprised that there is no interaction.

Gamma :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,683931402124997	,013855092881164	52
	Non math anxious	,676400347965257	,023806035596884	52
	Total	,680165875045127	,019747894960832	104
BT2	Math anxious	,684489104750677	,017714616578335	52
	Non math anxious	,678659249694734	,020790620236685	52
	Total	,681574177222706	,019441872913800	104
BT3	Math anxious	,676744653396495	,014222207026897	52
	Non math anxious	,684186285201805	,022468843691601	52
	Total	,680465469299150	,019081570066606	104

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	5,724E-5	,179	,836
	Greenhouse-Geisser	,000	1,938	5,907E-5	,179	,830
	Huynh-Feldt	,000	1,994	5,741E-5	,179	,836
	Lower-bound	,000	1,000	,000	,179	,673
BT * Mathanxiety	Sphericity Assumed	,003	2	,002	5,455	,005
	Greenhouse-Geisser	,003	1,938	,002	5,455	,005
	Huynh-Feldt	,003	1,994	,002	5,455	,005
	Lower-bound	,003	1,000	,003	5,455	,021
Error(BT)	Sphericity Assumed	,065	204	,000		
	Greenhouse-Geisser	,065	197,671	,000		
	Huynh-Feldt	,065	203,412	,000		
	Lower-bound	,065	102,000	,001		

Sphericity is not violated, so we take the values for sphericity assumed (first row without corrections). We can see that F (2, 204)= 5,455 is significant at 0,005. This means that there is a significant interaction between the two independent variables: target group (math anxiety) and Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	4,667E-6	1	4,667E-6	,013	,911
	Quadratic	,000	1	,000	,406	,525
BT * Mathanxiety	Linear	,003	1	,003	7,869	,006
	Quadratic	,001	1	,001	2,147	,146
Error(BT)	Linear	,038	102	,000		
	Quadratic	,028	102	,000		

According to the above table there is a linear component of the interaction of Back test and Math anxiety, meaning that average local efficiency increases/ decreases linearly over the back tests.

Tests of Between-Subjects Effects

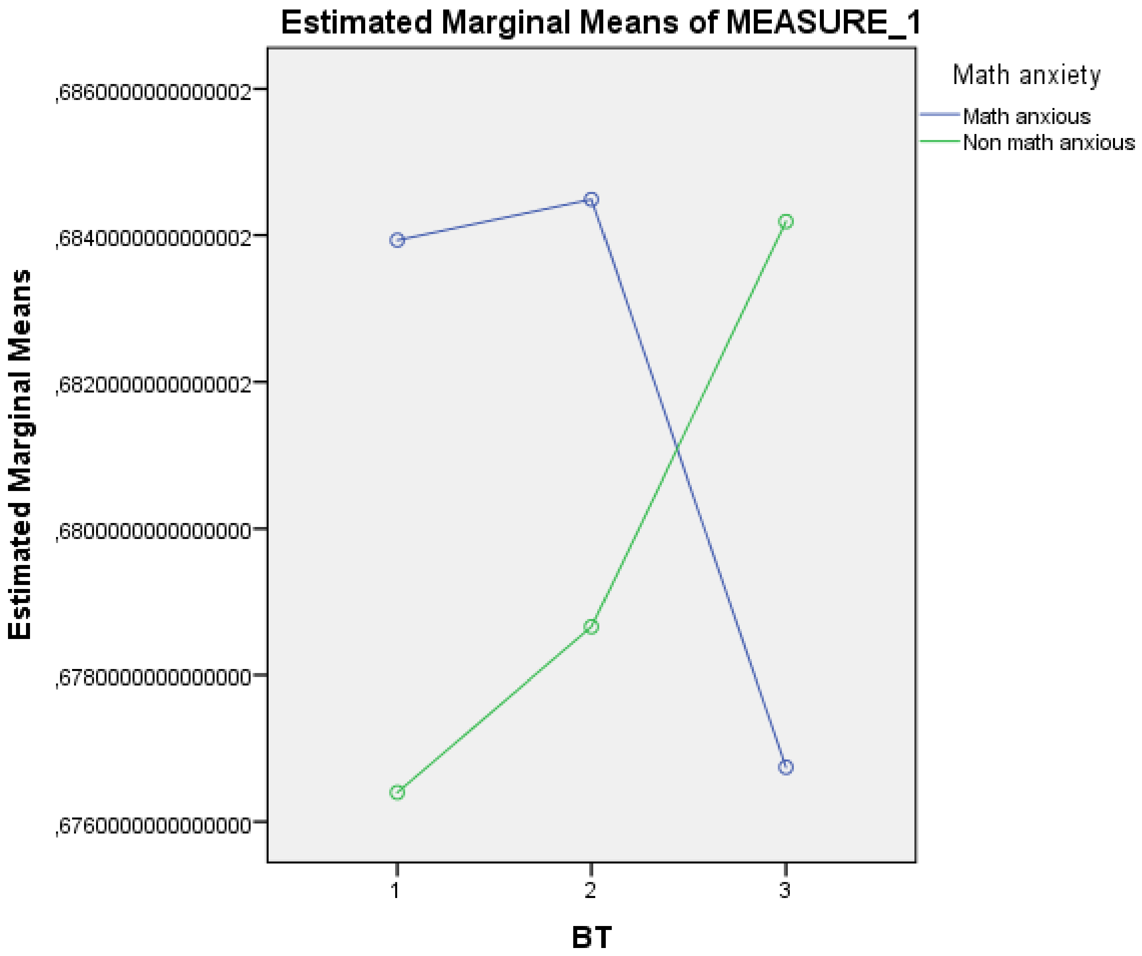
Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	144,581	1	144,581	310684,503	,000
Mathanxiety	,000	1	,000	,653	,421
Error	,047	102	,000		

The table above shows that the effect of the Group (math anxiety) is not statistically significant.

The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups are not generally far apart. The within subject test indicate that there is not a significant **back test** effect. Moreover, the interaction of **back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel. In the graph we see that the groups have non-parallel lines and they have a great gaps.



Theta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,681665980807798	,013549381795320	16
	Non math anxious	,681719614307776	,024788571174877	16
	Total	,681692797557787	,019878535087617	32
BT2	Math anxious	,677230894498881	,013376279641768	16
	Non math anxious	,674556155072340	,025153497648924	16
	Total	,675893524785611	,020091730984808	32
BT3	Math anxious	,678174615914236	,015394717516099	16
	Non math anxious	,688794972805323	,017374074438545	16
	Total	,683484794359779	,017183825309254	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,003	2	,002	4,495	,012
	Greenhouse-Geisser	,003	1,945	,002	4,495	,013
	Huynh-Feldt	,003	2,000	,002	4,495	,012
	Lower-bound	,003	1,000	,003	4,495	,036
BT * Mathanxiety	Sphericity Assumed	,003	2	,001	3,520	,031
	Greenhouse-Geisser	,003	1,945	,001	3,520	,033
	Huynh-Feldt	,003	2,000	,001	3,520	,031
	Lower-bound	,003	1,000	,003	3,520	,064
Error(BT)	Sphericity Assumed	,074	204	,000		
	Greenhouse-Geisser	,074	198,366	,000		
	Huynh-Feldt	,074	204,000	,000		
	Lower-bound	,074	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204) = 4,495 for Back test, is significant at p = 0,012. This means that ignoring whether participants are math anxious or non math anxious, there is an overall significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test. Additionally, F (2, 204) = 3,520 is significant at p = 0.031, which means that there is an overall significant interaction between the two independent variables target group and Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,000	1	,000	,517	,474
	Quadratic	,003	1	,003	7,668	,007
BT * Mathanxiety	Linear	,001	1	,001	4,491	,036
	Quadratic	,001	1	,001	2,745	,101
Error(BT)	Linear	,033	102	,000		
	Quadratic	,041	102	,000		

As far as Back test is concerned, it has a statistically significant quadratic component with $F(1,102) = 7{,}668$ being significant at $p=0{,}007$, reflecting the fact that the increase levels off, and even falls, at the last measurement. There is, also, a statistically significant linear component for the interaction with $F(1,102) = 4{,}491$ being significant at $p = 0{,}036$.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	144,420	1	144,420	417696,294	,000
Mathanxiety	,001	1	,001	1,604	,208
Error	,035	102	,000		

Table of Between-subjects effects indicates that the variable group is not statistically significant.

Pairwise Comparisons

Measure: Average local efficiency

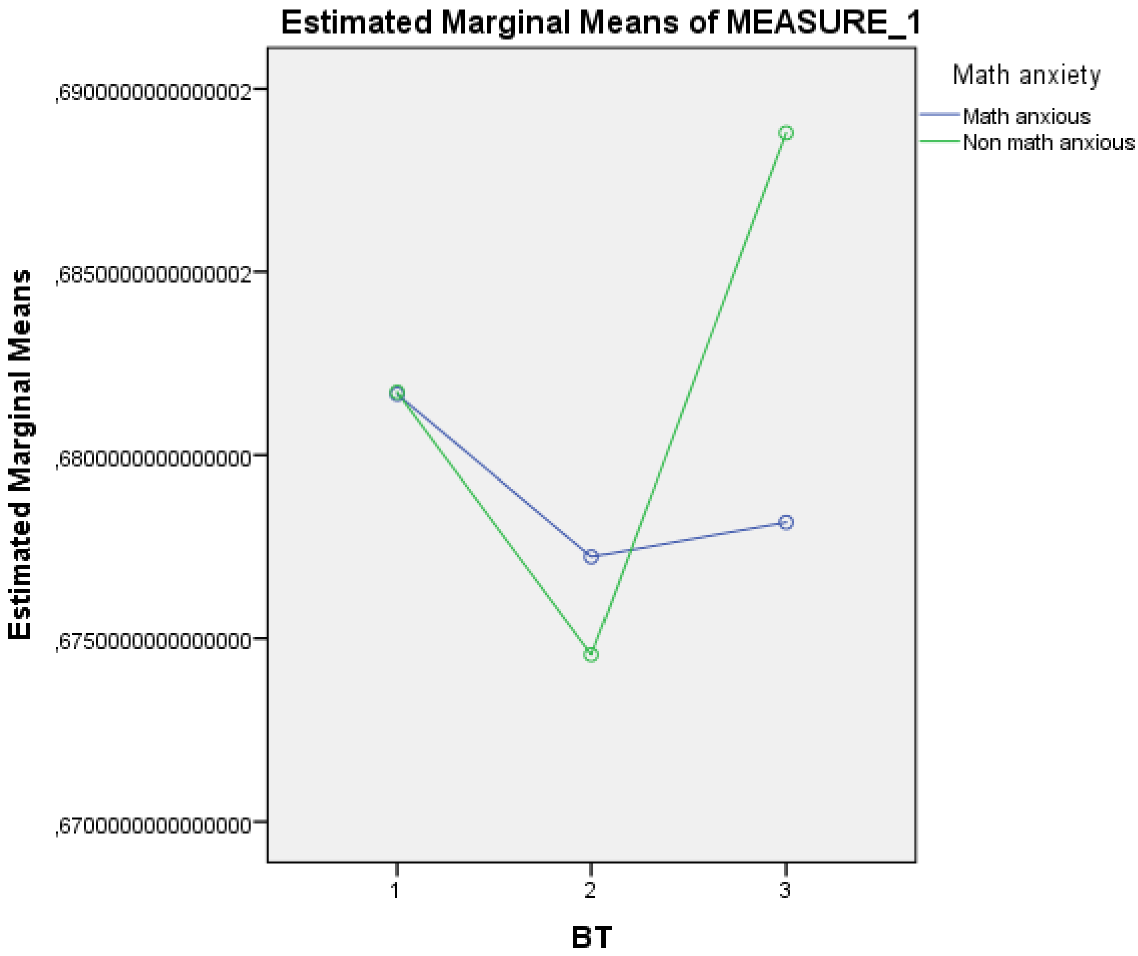
(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	,006	,003	,135	-,001	,013
	3	-,002	,002	1,000	-,008	,004
2	1	-,006	,003	,135	-,013	,001
	3	-,008*	,003	,012	-,014	-,001
3	1	,002	,002	1,000	-,004	,008
	2	,008*	,003	,012	,001	,014

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Post hoc tests with Bonferroni correction showed that the difference is found in the pair BT2-BT3, being statistically significant at p=0,012



The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups are not far apart. The within subject test indicate that there is a significant **Back test** effect, in other words, mean average local efficiency changes over back tests regardless the group. Moreover, the interaction of **Back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel.

Summary of the results :

About global efficiency :

A repeated measures ANOVA determined that mean global efficiency values do not differ significantly between back tests and between math anxious and non math anxious individuals for all six brain rhythms. Post-hoc tests with Bonferroni correction were not statistically significant, too. The F-values do not reach convenient levels of significance either with correction for sphericity or with no correction, implying that our results are trustworthy.

About density :

A repeated measures ANOVA determined that mean density values do not differ significantly between back tests and between math anxious and noon math anxious individuals. Post-hoc tests with Bonferroni correction were not statistically significant, too. For five brain rhythms (alpha 1, alpha 2, betta, delta, gamma), the F-values do not reach convenient levels of significance, either we correct for sphericity or not. For the theta brain rhytm, the assumption of sphericity is violated, so in ANOVA we take the row for the Greenhouse-Geisser correction, where significance is defined to $p<0,0005$. In this brain rhythm, the interaction of Backtest and math anxiety is significant without the correction, with $F(1,676, 50,272) = 6,876$, being significant at $p = 0,002$, therefore, it is not significant with the correction.

About Average local efficiency :

Alpha 1 :

A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency marginally differed significantly ($F(2,204)=3,013$, $p=0,05$) as Back tests get more difficult and is irrelevant to the group (math anxious-non math anxious). Post hoc tests using the Bonferroni correction revealed that Back test elicited a slight reduction in mean average local efficiency from Back test 1 to Back test 3 and from Back test 2 to Back test 3, which is not statistically significant (p=0,125 and p=0,086 respectively). (We will not assess this result as a significant one due to the marginal p-value problem).

Alpha 2 :

A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency differed significantly ($F(2,204)=9,759$, $p=0,000$) between Back tests, not related to group. Post hoc tests using the Bonferroni correction revealed that Back test elicited a slight increase in the mean average local efficiency from Back test 1 to Back test 2, which is statistically significant ($p=0,015$) and a slight decrease in the mean average local efficiency from Back test 2 to Back test 3, which is, also, statistically significant ($p=0,000$).Additionally, there is a statistically significant effect for the Group (math anxious-non math anxious) ($F(1,104)=11,424$, $p=0.001$). Post hoc tests with Bonferroni correction reveal that there is a statistically significant slight decrease in the mean average local efficiency from math anxious individuals to non math anxious ones.

Betta :

A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency differed significantly ($F(2,204)=7,518$, $p=0,001$) owing to the interaction of the group (math anxiety) and Back tests.

Delta :

A repeated measures ANOVA with sphericity assumed determined a statistically significant effect for the variable group (math anxiety)with $F(1, 102)=6,320$ being significant at 0,014, with math anxious having a slightly increased mean average local efficiency rather than non math anxious ones.

Gamma :

A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency differed significantly ($F(2,204)=5,455$, $p=0,005$) owing to the interaction of the group (math anxiety) and Back tests.

Theta :

A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency differed significantly ($F(2,204)=4,495$, $p=0,012$) between Back tests. Post hoc tests using the Bonferroni correction revealed that Back test elicited a slight increase in the mean average local efficiency from Back test 2 to Back test 3, which is statistically significant ($p=0,012$).

Additionally, A repeated measures ANOVA with sphericity assumed, determined that mean average local efficiency differed significantly ($F(2,204)=3,520$, $p=0,031$) owing to the interaction of the group (math anxiety) and Back tests.

Chapter 6

Discussion and importance of findings:

In our study, the basic notions of math anxiety and working memory are defined and various aspects of the influence of math anxiety in an individual's life are recorded. We have reported that math anxiety is an aversive emotional and motivational state occurring in threatening circumstances and according to Ashcraft it is experienced as a feeling of tension, apprehension, or fear that interferes with math performance. We have defined working memory as a cognitive system with a limited capacity that is responsible for the transient holding, processing, and manipulation of information.

Additionally, we constructed the brain networks for individuals who are either math anxious, or non math anxious and we investigated network metrics, as well as whether math anxiety and increased difficulty in Back tests influences the efficiency (local and global) and the density of the brain network of individuals.

According to the results, our networks have small-world properties, a structure that enables optimal information flow, and a relatively high modularity, as well as high efficiency, characteristics of the small-world structure.

In addition, the results are indicative that there is no intervention neither by math anxiety, nor by working memory difficulty in density and global efficiency of the brain networks, however, average local efficiency is influenced by math anxiety and Back test difficulty. In Betta and Gamma bands, we have a similar pattern : the interaction of group (math anxious-non math anxious) and increasing difficulty in Back tests influences mean average local efficiency. Particularly, in Alpha 2 band, increasing difficulty in Back tests has a statistically significant effect on mean average local efficiency, and the differences are between BT1-BT2 and BT2-BT3. Additionally, mean average local efficiency differs significantly between the groups. In Delta band, mean average local efficiency differs significantly between the groups. In Theta band, increasing difficulty in Back tests influences mean average local efficiency, regardless the "group" factor, and the difference is between BT2-BT3. Moreover, the interaction of group (math anxious-non math anxious) and increasing difficulty in Back tests has a significant effect on mean average local efficiency.

The patterns we identified in mean average local efficiency may imply biomarkers for assessing anxiety and guiding a way of what should be done towards an optimal state (e.g. if a specific brain network pattern is identified, non-invasive methods like neurofeedback could be used to help people overcome math anxiety (Klados & Bamidis, 2014)).

Additionally, further analysis of our results and combination with the statistical analysis of a few more network metrics such as average path length and clustering coefficient can provide very important evidence for the most of the problems math anxiety causes (see Chapter 2), and solutions can be formulated based on that evidence.

Moreover, we noticed that in almost all bands, math anxious mean average local efficiency increases from Back test 1 to Back test 2 and then decreases. A possible interpretation for this is that as local efficiency of a node is typical of how well information is exchanged by its neighbors when the node itself is removed, the increase of the levels of local efficiency on average possibly means that math anxious individuals use a mechanism(i.e motivational factors) to outweigh their loss of resources. This theory is consistent with the findings of Ashcraft.Ashcraft designed a test which was increasingly more mathematically challenging, and noticed that in the first parts even high math anxious individuals responded accurately, while on the latter and more difficult part of the test, Ashcraft noticed a stronger negative correlation between math anxiety and accuracy of the responses.

To best of our knowledge, little is known about mechanisms that math anxious people use to balance the loss of resources and reach convenint levels of performance. The study of such mechanisms would be a great challenge for Neuroscience. Our results are possibly implying the existence of such mechanisms. Further research could be made on how such mechanisms are created, and how their effects can be reinforced.

There is a variety of results and discussion that can be done about math anxiety and its effects. In the following last part, there are given some future innovative research directions that derived through this study to develop the subject more.

Future research :

It would be of great interest to further analyze the results of this study and the centrality measures computed. We could compute Entropy and Mutual information measures for various centralities in each network and make comparisons for the homogeneity of the centralities of the networks. Additionally, we could compare the network of math anxious and non math anxious brains and determine whether entropy of the network could be used as a diagnostic means for math anxiety (proportional to the fact that entropy is used as a diagnostic means of neuropathic diseases).

A second interesting field of research would be to investigate whether entropy is relieved by music, and which are the mechanisms that enable the interaction. Music stimulates the brain in ways that nothing else can," says Kamile Geist, an assistant professor of music therapy. "Creating and reacting to a steady beat is innate. The patterns within different rhythms and melody lines enhance an infants' level of awareness and promote active engagement immediately." Kamile Geist created a program called MathSTAAR which tries to teach teachers how to insert music in the teaching procedures, so that they have fewer anxiety incidents (http://medicalxpress.com/partners/ohio-university/)

Additionally, math anxiety is a feeling that can be analyzed in the context of neuroeconomics (see Appendix A). It is quite possible that math anxiety is a key factor in research for neurofinance on how to enable efficient information processing in the brain network, and thus improve investment and trading decisions. Our results and the fact that math anxiety and difficulty in Back tests influence mean average local efficiency in the network, could be a first step and a motivation to search further for answers.

Finally, as mentined before, it would be of a great interest to further investigate the strategies used by anxious individuals when their processing becomes inefficient. Typically, they increase effort or motivation to maintain their performance towards a task. Therefore, anxious individuals sometimes use other strategies. For instance, according to Klein & Barnes (1994) math anxious individuals use an approach that saves capacity related to analogical reasoning tasks, by using suboptimal strategies to eliminate demands on the central executive. Another strategy implies persistent searching for increased evidence requirements before responding. Generally, anxious individuals set a more strict decision criterion than non anxious ones. To the best of my knowledge, the research about factors determining the strategy used by anxious individuals to respond to a given task, remain in a primary level. Results from such a research will be proven very helpful in various fields which math anxiety influences (see Chapter 2), as well as help finding solutions for math anxiety, and strategies to deal with math anxious individuals.

Appentices

I. Appendix A

Neuroeconomics and neuromarketing

Neuroeconomics is an interdisciplinary field that combines mathematical models and computer science with social studies, neuroscience, theoretical biology and economics. As a field, neuroeconomics studies especially decision making, the ability of humans to examine different alternatives and pick out one to follow. Classical economic models use the concept of utility and rational agents in a single perspective way, and thus many theories cannot be explained (e.g.heuristics or framing-a set of concepts and theoretical approaches about the way individuals, particular groups and societies organize, perceive, make choices and communicate with each other). (Loewenstein et. al, 2008) To mitigate the problem, behavioral economics arise, to take into account social, cognitive and emotional factors for the conception of economic behavior.

People make decisions based on risk factors. Risk is defined as an uncertainty about future possible outcomes, each of which is possible as a certain probability implies. (Mohr et. al, 2010). Daniel Bernoulli in 1738, proposed the so-called "utility maximization" to understand and reach conclusions about the decision making under uncertainty. The theory assumes that agents are rational and they make choices so as to maximize the utility they gain from them. (Loewenstein et. al, 2008) Despite the fact that Bernoulli's theory of utility maximization was a quite adequate model, experience and life have shown that there are anomalies in the principle, plus common behavioral patterns are opposing to it. For instance, the tendency of humans (and animals) to be risk averse or risk seeking and the tendency to overestimate small probabilities or underestimate bigger ones, are anomalies for the principle of utility maximization. prospect theory of AmosTversky and Daniel Kahneman, is an alternative model of behavioral economics that takes the problem of the anomalies of utility maximization into consideration (Loewenstein et. al, 2008). There are multiple brain regions involved in the decision making under risk. Paticularly, there is an increase in activity in the BA8 area of the frontomedian cortex(Volz et.al. (2003.), as well as in mesial prefrontal cortex (Knutson et.al, 2005)and in frontoparietal cortex (Paulus et al. 2001). Additionally, when individuals are involved in situations with known risk (e.g. in games like "double or nothing" where either you win double the amount of gambling or you lose it all), they show increased activation in the right insula when they take the gamble. (Paulus et al. 2001). Insular cortex is considered to make simulations about possible negative outcomes in a gambling situation. There is, also, evidence supporting that the neurotransmitter domamine, spreads information about uncertainty in the cortex. Generally, domaminergic neurons are activated when a reward occurs. Experiments with animals show that in monkeys, activity of dopamine neurons increases with uncertainty (Fiorillo et. al, 2003) while rats with lesions in nucleus accumbens (a necessary part for the reward pathway of dopamine)seem to be far more risk averse than normal rats. (Cardinal et. al, 2005)

Moreover, people show extreme loss aversion (e.g. losing an amount of money costs higher than the value when one gains the same amount of money). Neuroeconomic studies are trying to declare whether the decisions are based in a single system, or they are driven by two systems, one which supports reasonable comparison between various options, and another one more emotional and impulsive that is based in the fear for potential loss. So far, the results are controversial with the one view claiming that no areas are found to be related with negative emotions about loss aversion (Tom et. al, 2007) and others claiming that people with lesions in amygdala show deficiency in loss aversion, although they show normal risk aversion.(De Martino et. al, 2010). Additionally, studies have determined that stress responses like skin conductance, heart rates and pupil dilation are higher in monetary loss, rather than money gain, supporting the hypothesis that losing an amount of money is experienced more intensely than gaining the same amount (Sokol-Hessner et. al, 2009; Hochman et. al, 2011).

Another aspect neuroeconomic studies take into account is the perspective of social decision making, meaning that people often take decisions based on emotional and personal factors, driven by altruism, cooperation or punishment rather that trying to do the best for themselves. For instance, there is the prisoner's dilemma (Stanford Encyclopedia of Philosophy, 1997) where the payoff for a particular decision is not inclusively based on the individual's choices, but also based on the way the other individual is playing the game. Each payoff for each individual according to their choices is shown in the following table.

	C	D
C	2 2	3 0
D	0 3	1 1

Fig.9 Source :en. wikipedia.org

The optimal solution for both individuals is to cooperate rather than seek the perfect result for themselves. (Rilling et. al, 2002) An important aspect for this type of interactions is trust. Generally the likelihood of cooperating with another individual is possitevely correlated to how much you trust them and the feelings you may have for them (e.g. if you believe they are going to defect against you, you will probably not select the option to cooperate with them).Trust is supported by the hormone oxytocin which is involved in maternal behavior and pair-bonding not only in humans, but, also in many other species. Elevated levels of oxytocin make people trust others more, so oxytocin seems to be involved in social risk taking.(Kosfeld et. al, 2005)

Neuroeconomics have brought a new era in economics and created new fields like neurofinance, neuroinvesting and neurotrading. Elise Payzan states that portfolio managers and traders have to process information for rapidly changing situations. Little is known about how organisational processes and individual's decision making is done under that circumstances. Identifying key factors that enable efficient information through neurofinance research can improve investment and trading decisions in individual and organizational level. (Payzan et. al, 2013).

Finally, special reference should be done in a great subfield of neuroeconomics : Neuromarketing. Neuromarketing is an emerging branch of marketing which has derived from the collaboration of neuroscience research and business. Neuromarketing was first indroduced in an article published in 2002 from Brighthouse, an Atlanta marketing firm, which established the use of fMRI for marketing research purposes and now has over 500 famous brands as clients. Through neuromarketing research we can acquire a better understanding of the subconscious reaction of individuals towards advertising, brands and products, as well as how people's brain manages the information from messages or images, and how they make decisions. Such a knowledge provide companies with the essential feedback for market research and helps them design the next marketing campaign based on the brain responses of their target group. There are many companies worldwide which hire neuromarketing agencies to conduct intelligent research declare consumers' underpinnings of buying decisions.

A significant neuromarketing study conducted by Daimler Chrysler in 2002 granted a better understanding of people's reactions to cars (Hunt, 2008). The results have shown thae pictures of high-performance cars such as the Ferrari 360 Modena and the BMW Z8 excited brain areas relavant to concepts of wealth and social power. The company took pure emotional responses that no focus group or survey could reveal (Hunt, 2008). According to Lindstrom (2008), neuromarketing studies can reveal unexpected results confirming that people do not always know what lies beneath the unconscious part of their minds. For instance, according to Lindstom's studies not only warning pictures on packages of cigarettes do not prevent people from buying cigarettes, but, also, they stimulate some devisions of the brain to light up a cigarette. However, when Lindstom asked respondents to recall the long-term negative consequences of smoking in a study conducted by the

Department of Psychiatry at Yale University, the subject's craving for smoking was eliminated. Brain scans demonstrated an increased motion in dorsolateral prefrontl cortex, the region responsible for goal setting, planning, and controlling behavior. The Hollywood Film Industry, also, took advantage of neuromarketing techniques. James Cameron used fMRI scans and demonstrated that watching his film in 3-D activated much more neurons than watching it in a conventional form.(Desaulniers, 2013).

One of the greatest studies of neuromarketing is a study from a group of Read Montague, published in Neuron (McClure et. al, 2004), which was called "The Pepsi challenge", a blind taste of Coca Cola and Pepsi. The brain scans of 67 individuals were studied during the challenge. Half of the individuals chose Pepsi, as it seem to produce stronger response in their brains than Coke, and stimulated the ventromedial prefrontal cortex, a region that is found to process feelings of reward. When the individuals were informed they were drinking Coke, the three quarters said that Coke had a better taste, and their brain activity had change, too, with a higher stimulation of the lateral prefrontal cortex (where high level cognitive powers are established) and the hippocampus (a division related to memory). The above experiment implies that subjects were thinking about Coke and relating it with other experiences, memories and feelings. The results indicate that Pepsi could possibly have half the market share, however consumers prefer Coke not totally about taste preferences, but due to the connection of feelings and experiences with the Coke brand. (Samuel et. al, 2004)

Danish marketer Martin Lindstrom has made neuromarketing a popular field through his writing Buyology: Truth and Lies About Why We Buy. Lindstrom and Oxford University researchers scanned the brains of more than 2,000 subjects around the world during watching advertising and marketing materials such as logos, product placements, health warnings, and subliminal images. The study resulted in the fact that branding can emphasize and optimize all brand’s signals especially the direct ones . Further, Lindstrom has determined that hearing and smelling is more powerful than seeing, although other studies claim that vision is the most influential sense. Additionally, Lindstrom discovered that emotional engagement is a prominent influential factor, as buying decisions of individuals are mostly based on emotional factors rather than rational ones. Lindstrom concludes that emotional aspects of ads are more powerful and influential than the visual ones (Lindstrom, 2008).

II.Appendix B

RESULTS in detail

Global efficiency

Global efficiency alpha 1

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,876569122261421	,020012477925101	16
	Non math anxious	,881485675690934	,016859887855761	16
	Total	,879027398976177	,018373110040329	32
BT2	Math anxious	,872778809115267	,020116716270504	16
	Non math anxious	,875282121017659	,020757006380114	16
	Total	,874030465066463	,020147173318444	32
BT3	Math anxious	,869522637379072	,016278524527186	16
	Non math anxious	,870808210625000	,013818528119316	16
	Total	,870165424002036	,014867536393814	32

Tests of Within-Subjects Effects

Measure: Global efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
Backtest	Sphericity Assumed	,001	2	,001	1,714	,189
	Greenhouse-Geisser	,001	1,916	,001	1,714	,190
	Huynh-Feldt	,001	2,000	,001	1,714	,189
	Lower-bound	,001	1,000	,001	1,714	,200
Backtest * MA	Sphericity Assumed	5,464E-5	2	2,732E-5	,074	,929
	Greenhouse-Geisser	5,464E-5	1,916	2,852E-5	,074	,922
	Huynh-Feldt	5,464E-5	2,000	2,732E-5	,074	,929
	Lower-bound	5,464E-5	1,000	5,464E-5	,074	,787
Error(Backtest)	Sphericity Assumed	,022	60	,000		
	Greenhouse-Geisser	,022	57,468	,000		
	Huynh-Feldt	,022	60,000	,000		
	Lower-bound	,022	30,000	,001		

F(1.714, 2) is not significant. This means that there is no signifficant difference between the two groups of participants (math anxious and non math anxious ones). For the same reason, there is no significant interaction between the two independent variables (math anxiety and back test) on the dependent variable.

Tests of Between-Subjects Effects

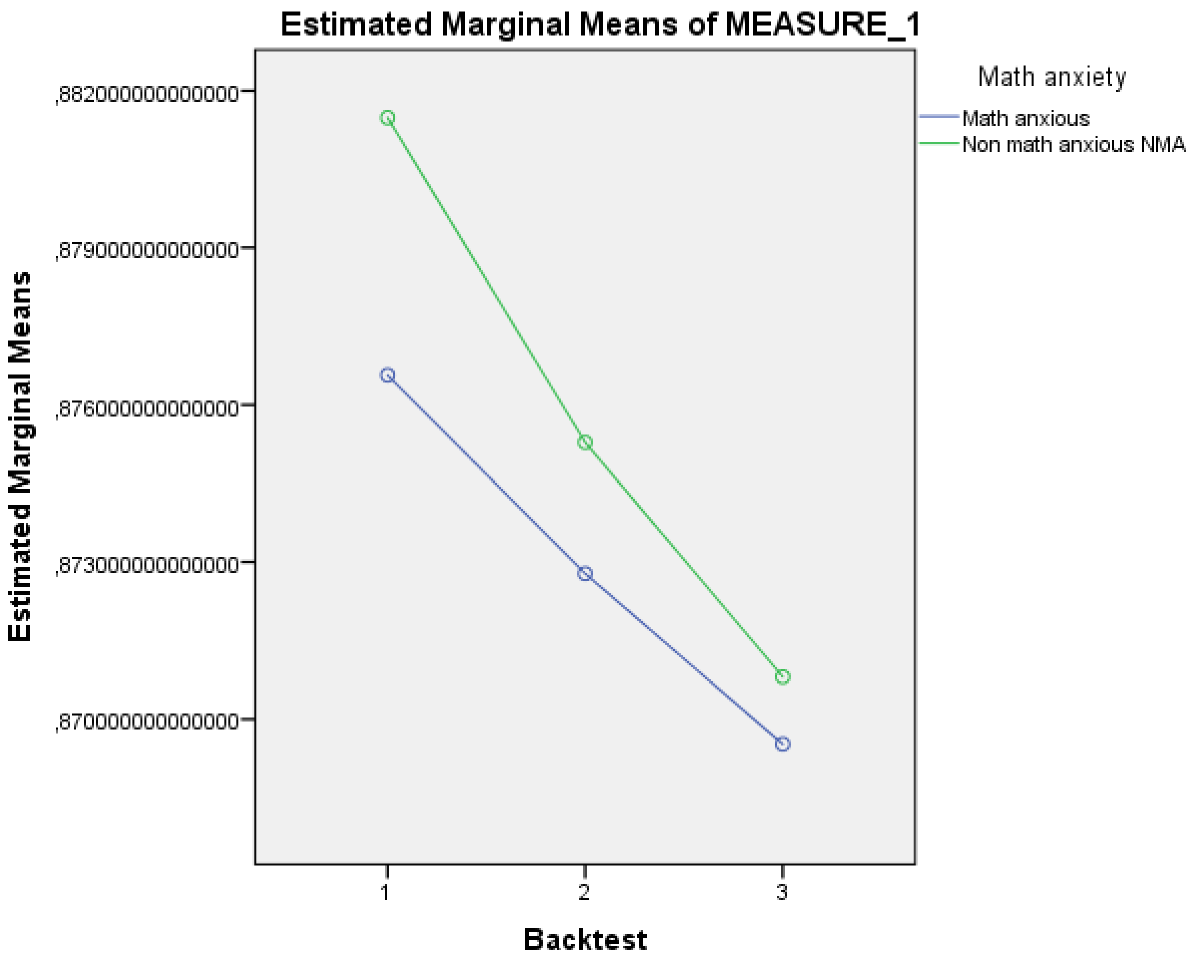
Measure: Global efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	73,401	1	73,401	292619,628	,000
MA	,000	1	,000	,806	,377
Error	,008	30	,000		

This output indicates that there is no significant main effect for math anxiety, which means there is no statistically significant difference in the global efficiency between math anxious and non math anxious individuals.

The top line connects the three means for Non math anxious students, while the bottom line connects the three means for math anxious students. We can see that there is a little difference between the two groups in the first level of difficulty in the back test, with non math anxious students showing greater efficiency, whereas the gap gets smaller when we reach the third level of difficulty. The group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.



Global efficiency alpha2 :

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,872787135670027	,015440464311317	16
	non math anxious	,880086733768176	,027509716941778	16
	Total	,876436934719101	,022255234994623	32
BT2	math anxious	,878122468929687	,024821414361333	16
	non math anxious	,864429844470175	,018128836601784	16
	Total	,871276156699931	,022483874958893	32
BT3	math anxious	,867484372059397	,020874873838760	16
	non math anxious	,875163308751046	,019189532276945	16
	Total	,871323840405222	,020105934087610	32

Tests of Within-Subjects Effects

Measure: globalefficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,000	,638	,532
	Greenhouse-Geisser	,001	1,503	,000	,638	,490
	Huynh-Feldt	,001	1,618	,000	,638	,501
	Lower-bound	,001	1,000	,001	,638	,431
BT * MA1NMA2	Sphericity Assumed	,002	2	,001	2,714	,074
	Greenhouse-Geisser	,002	1,503	,002	2,714	,091
	Huynh-Feldt	,002	1,618	,001	2,714	,087
	Lower-bound	,002	1,000	,002	2,714	,110
Error(BT)	Sphericity Assumed	,026	60	,000		
	Greenhouse-Geisser	,026	45,103	,001		
	Huynh-Feldt	,026	48,542	,001		
	Lower-bound	,026	30,000	,001		

The within subjects table and between subjects table have no signnificant interactions, so there is no need to further search for dependencies.

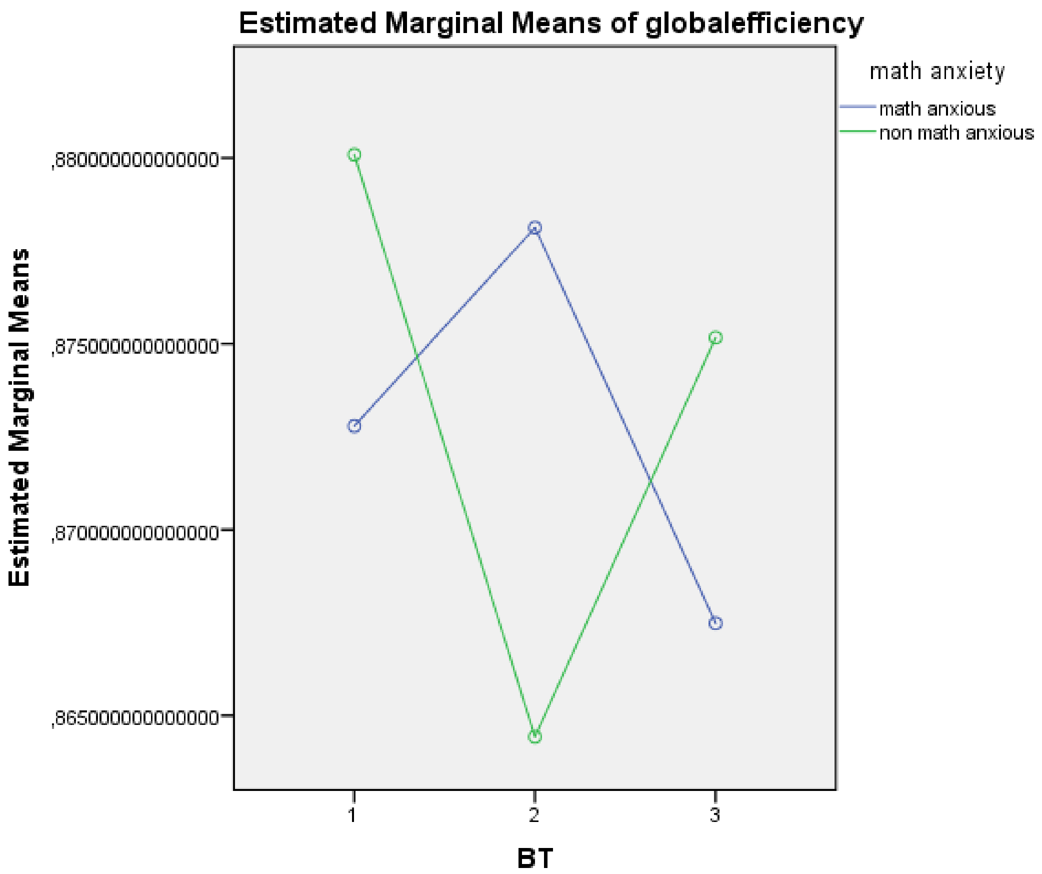
Tests of Between-Subjects Effects

Measure: globalefficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	73,166	1	73,166	149337,748	,000
MA1NMA2	4,410E-6	1	4,410E-6	,009	,925
Error	,015	30	,000		

In the graph below, the green line connects the three means for the students NMA whereas the blue line connects the three means for the students MA (each of the three means stands for each of the three back tests). We can see that there is an interaction of MA and Back test, which is not significant as indicated from within subjects table. The variable group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.



Global efficiency betta

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,869726224446643	,019315276766861	16
	non math anxious	,864422838298433	,018783307745536	16
	Total	,867074531372538	,018934007409229	32
BT2	math anxious	,878441103048676	,018169375362270	16
	non math anxious	,871804515276555	,017315732689414	16
	Total	,875122809162616	,017781620061585	32
BT3	math anxious	,872803559874096	,014508037693573	16
	non math anxious	,864925024031886	,012407108421199	16
	Total	,868864291952991	,013869045450023	32

Tests of Within-Subjects Effects

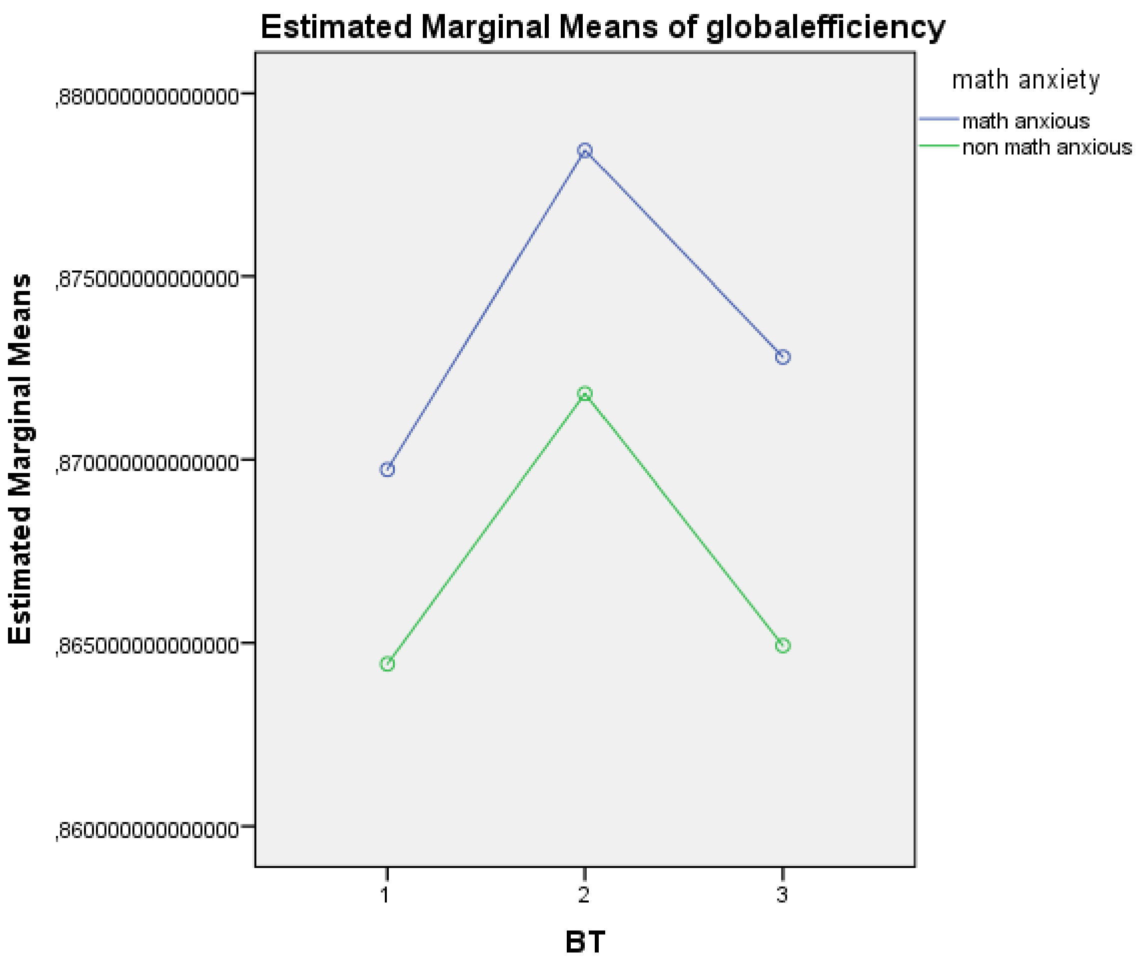
Measure: globalefficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,001	2,796	,069
	Greenhouse-Geisser	,001	1,943	,001	2,796	,071
	Huynh-Feldt	,001	2,000	,001	2,796	,069
	Lower-bound	,001	1,000	,001	2,796	,105
BT * MA1NMA2	Sphericity Assumed	2,654E-5	2	1,327E-5	,065	,937
	Greenhouse-Geisser	2,654E-5	1,943	1,366E-5	,065	,933
	Huynh-Feldt	2,654E-5	2,000	1,327E-5	,065	,937
	Lower-bound	2,654E-5	1,000	2,654E-5	,065	,801
Error(BT)	Sphericity Assumed	,012	60	,000		
	Greenhouse-Geisser	,012	58,287	,000		
	Huynh-Feldt	,012	60,000	,000		
	Lower-bound	,012	30,000	,000		

None of the interactions is statistically significant to influence the global efficiency of the individuals' brain network.

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	72,722	1	72,722	161105,792	,000
MA1NMA2	,001	1	,001	2,320	,138
Error	,014	30	,000		

We can clearly see that the lines for the two groups are rather far apart. The within subject test indicate that there is not a significant **Back test** effect. We can see that the efficiency of both the two groups is ascending and descending proportionally, with the math anxious individuals being a little bit more efficient than the non math anxious ones. The variable group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.



Global efficiency delta

Descriptive Statistics

	MA1NMA2	Mean	Std. Deviation	N
BT1	Math anxious	,870763822475635	,017580966932585	16
	Non math anxious	,867615921827720	,013583106907848	16
	Total	,869189872151677	,015536784760205	32
BT2	Math anxious	,873876325534041	,023094802821642	16
	Non math anxious	,866198391998242	,010522974910434	16
	Total	,870037358766142	,018079706215572	32
BT3	Math anxious	,872592163487997	,018841515985306	16
	Non math anxious	,882280243740346	,025214387642430	16
	Total	,877436203614172	,022441603231726	32

Tests of Within-Subjects Effects

Measure: globalefficiency

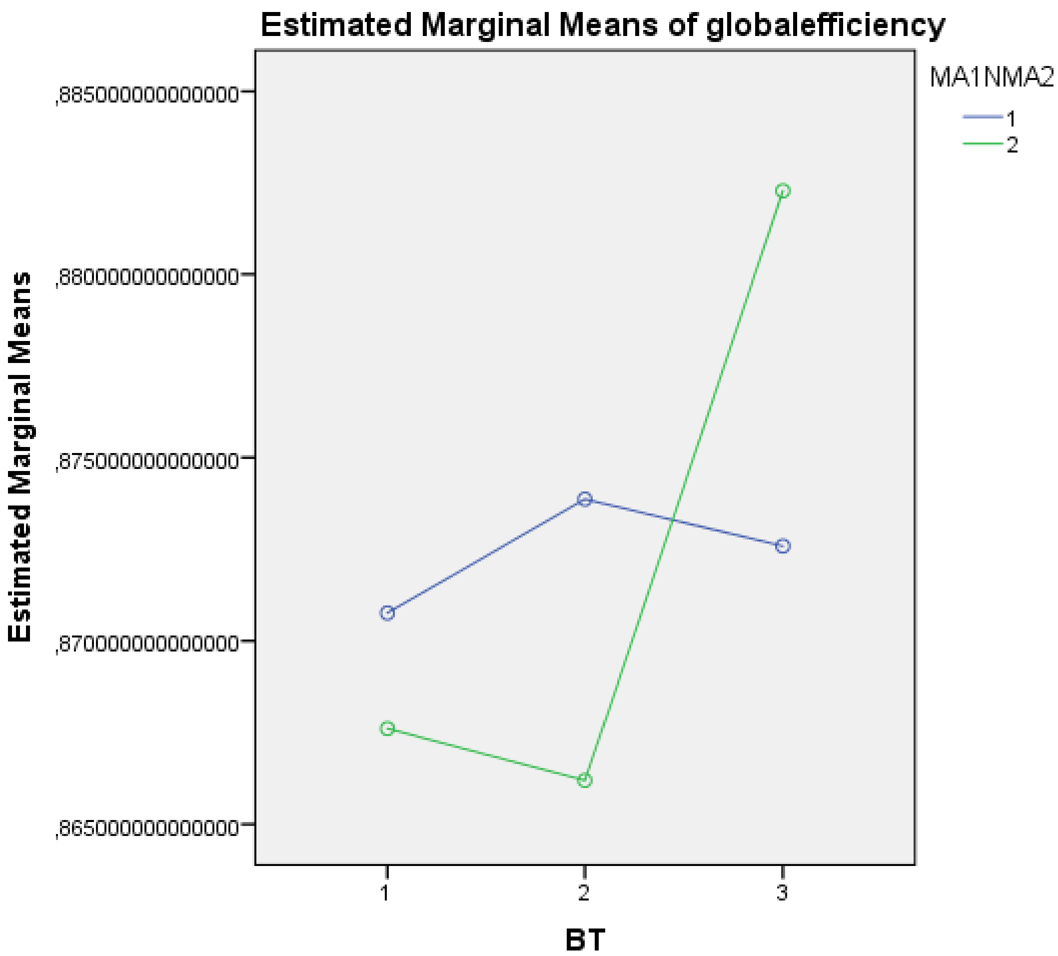
Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,001	1,955	,151
	Greenhouse-Geisser	,001	1,803	,001	1,955	,155
	Huynh-Feldt	,001	1,975	,001	1,955	,151
	Lower-bound	,001	1,000	,001	1,955	,172
BT * MA1NMA2	Sphericity Assumed	,001	2	,001	1,927	,155
	Greenhouse-Geisser	,001	1,803	,001	1,927	,159
	Huynh-Feldt	,001	1,975	,001	1,927	,155
	Lower-bound	,001	1,000	,001	1,927	,175
Error(BT)	Sphericity Assumed	,020	60	,000		
	Greenhouse-Geisser	,020	54,087	,000		
	Huynh-Feldt	,020	59,254	,000		
	Lower-bound	,020	30,000	,001		

None of the interactions is statistically significant to influence the global efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: globalefficiency
Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	73,034	1	73,034	187052,440	,000
MA1NMA2	3,452E-6	1	3,452E-6	,009	,926
Error	,012	30	,000		



From the graph, we can deduce that math anxious individuals, are more efficient in BT1 and BT2, and there is a great increase in the efficiency of the brain network of non math anxious ones as far as BT3 is concerned. The within subject test indicate that there is not a significant **Back test** effect. The variable group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.

Global efficiency gamma

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,873776664414608	,024267494077805	16
	non math anxious	,872386685964295	,017036067961637	16
	Total	,873081675189452	,020637063062244	32
BT2	Math anxious	,878834664502703	,017492001438457	16
	non math anxious	,876320541583560	,024099528408624	16
	Total	,877577603043132	,020753489617206	32
BT3	Math anxious	,868533102768241	,019234584890332	16
	non math anxious	,884516127396670	,021349961499810	16
	Total	,876524615082456	,021575455207238	32

Tests of Within-Subjects Effects

Measure: globalefficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	,000	,409	,666
	Greenhouse-Geisser	,000	1,658	,000	,409	,628
	Huynh-Feldt	,000	1,801	,000	,409	,645
	Lower-bound	,000	1,000	,000	,409	,527
BT * MA1NMA2	Sphericity Assumed	,002	2	,001	1,988	,146
	Greenhouse-Geisser	,002	1,658	,001	1,988	,155
	Huynh-Feldt	,002	1,801	,001	1,988	,151
	Lower-bound	,002	1,000	,002	1,988	,169
Error(BT)	Sphericity Assumed	,026	60	,000		
	Greenhouse-Geisser	,026	49,726	,001		
	Huynh-Feldt	,026	54,026	,000		
	Lower-bound	,026	30,000	,001		

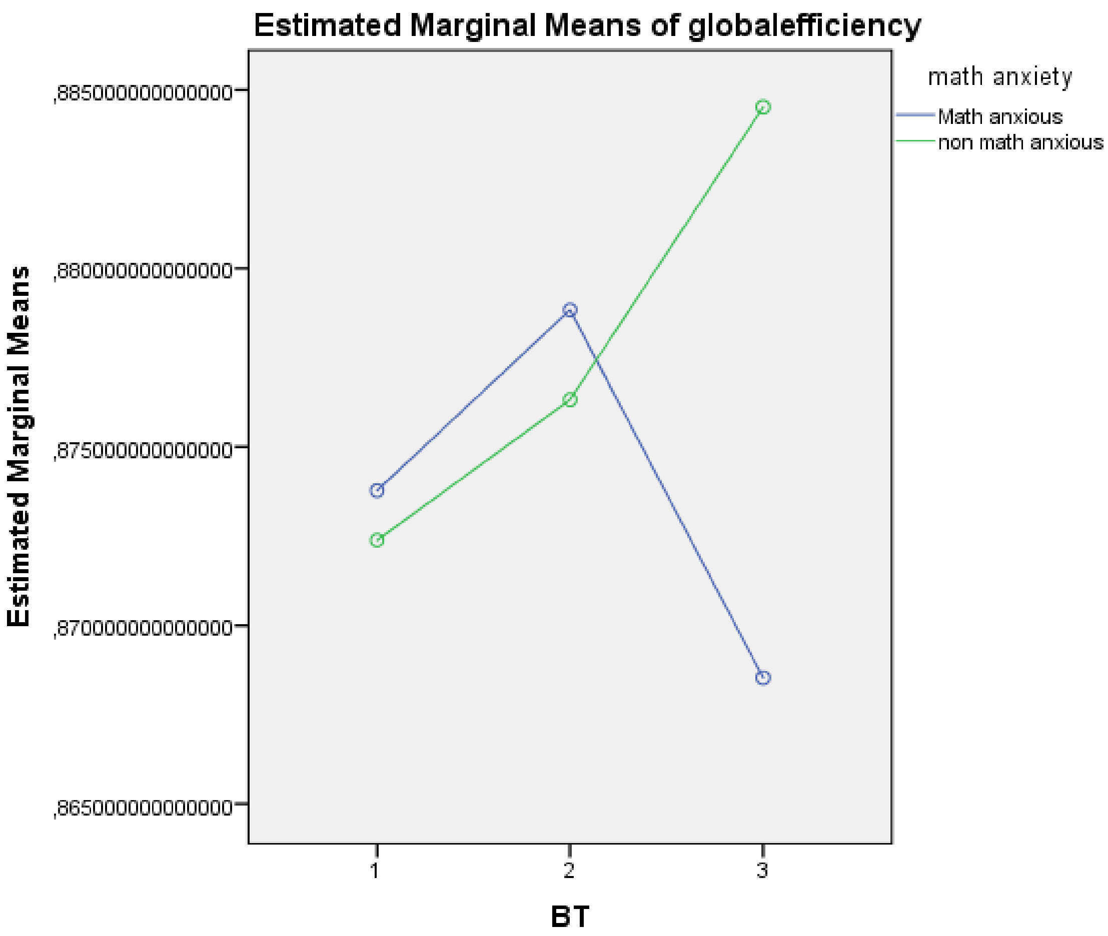
None of the interactions is statistically significant to influence the global efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: globalefficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	73,622	1	73,622	171135,135	,000
MA1NMA2	,000	1	,000	,904	,349
Error	,013	30	,000		



From the graph below, we can deduce that math anxious individuals, are more efficient in BT1 and BT2, and there is a great increase in the efficiency of the brain network of non math anxious ones as far as BT3 is concerned. The within subject test indicate that there is not a significant **Back test** effect. The variable group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.

Global efficiency theta

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,870763822475635	,017580966932585	16
	non math anxious	,867615921827720	,013583106907848	16
	Total	,869189872151677	,015536784760205	32
BT2	math anxious	,873876325534041	,023094802821642	16
	non math anxious	,866198391998242	,010522974910434	16
	Total	,870037358766142	,018079706215572	32
BT3	math anxious	,872592163487997	,018841515985306	16
	non math anxious	,882280243740346	,025214387642430	16
	Total	,877436203614172	,022441603231726	32

Tests of Within-Subjects Effects

Measure: globalefficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,001	1,955	,151
	Greenhouse-Geisser	,001	1,803	,001	1,955	,155
	Huynh-Feldt	,001	1,975	,001	1,955	,151
	Lower-bound	,001	1,000	,001	1,955	,172
BT * MA1NMA2	Sphericity Assumed	,001	2	,001	1,927	,155
	Greenhouse-Geisser	,001	1,803	,001	1,927	,159
	Huynh-Feldt	,001	1,975	,001	1,927	,155
	Lower-bound	,001	1,000	,001	1,927	,175
Error(BT)	Sphericity Assumed	,020	60	,000		
	Greenhouse-Geisser	,020	54,087	,000		
	Huynh-Feldt	,020	59,254	,000		
	Lower-bound	,020	30,000	,001		

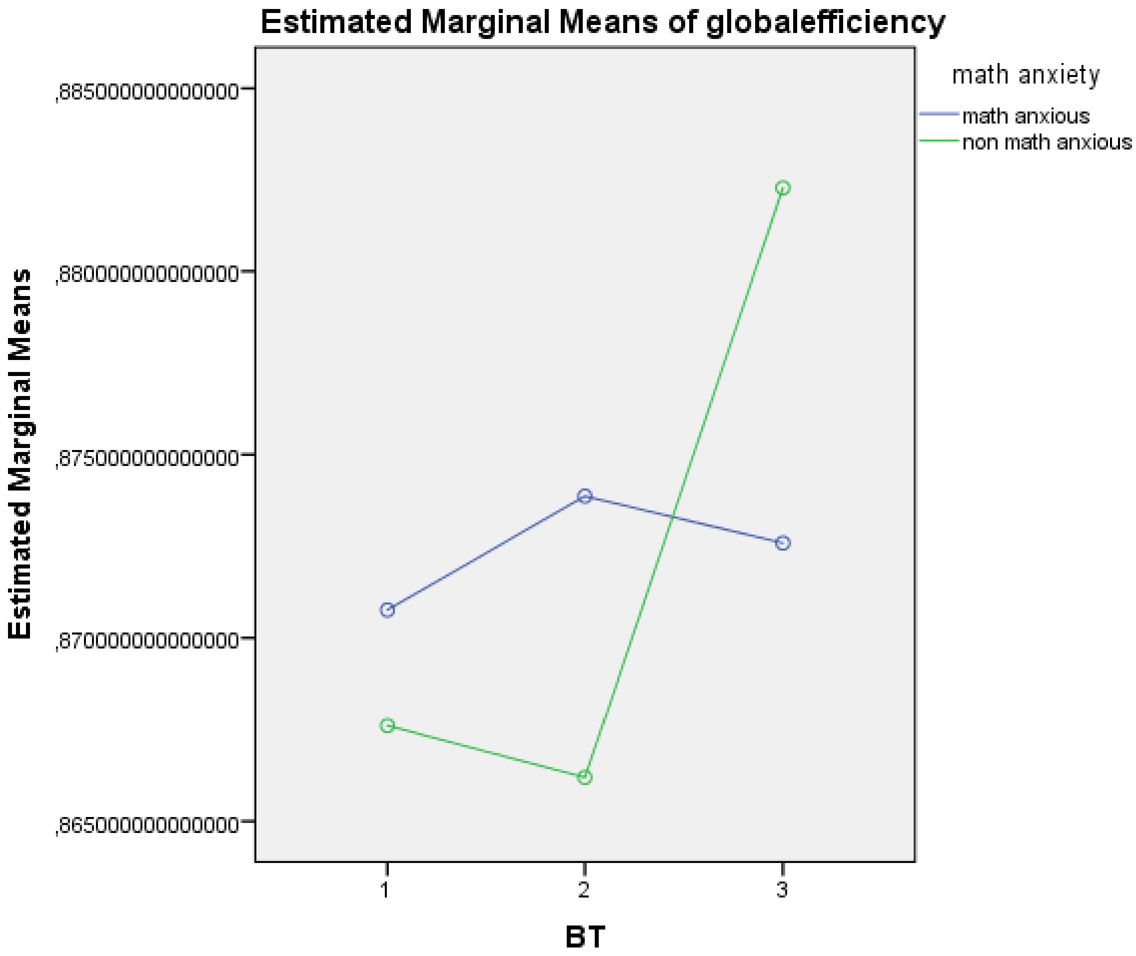
None of the statistical tests above provides statistically significant results to be analyzed.

Tests of Between-Subjects Effects

Measure: globalefficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	73,034	1	73,034	187052,440	,000
MA1NMA2	3,452E-6	1	3,452E-6	,009	,926
Error	,012	30	,000		



From the graph, we can deduce that math anxious individuals, are more efficient in BT1 and BT2, and there is a great increase in the efficiency of the brain network of non math anxious ones as far as BT3 is concerned. The within subject test indicate that there is not a significant **Back test** effect. The variable group is not significant as indicated from the between subjects test, and that is the reason why the two lines are not very far.

Density

Density Alpha1 :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,500235671191554	,011041571335417	16
	Non math anxious	,496323529411765	,007264261362826	16
	Total	,498279600301659	,009406116210245	32
BT2	Math anxious	,503723604826546	,012566521851023	16
	Non math anxious	,501649698340875	,010189720299300	16
	Total	,502686651583710	,011303192202610	32
BT3	Math anxious	,500047134238311	,009842399450508	16
	Non math anxious	,507400075414781	,008202404826704	16
	Total	,503723604826546	,009663382880959	32

Tests of Within-Subjects Effects

Measure: density

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,000	2,236	,116
	Greenhouse-Geisser	,001	1,942	,000	2,236	,117
	Huynh-Feldt	,001	2,000	,000	2,236	,116
	Lower-bound	,001	1,000	,001	2,236	,145
BT * MA1NMA2	Sphericity Assumed	,001	2	,000	2,444	,095
	Greenhouse-Geisser	,001	1,942	,000	2,444	,097
	Huynh-Feldt	,001	2,000	,000	2,444	,095
	Lower-bound	,001	1,000	,001	2,444	,128
Error(BT)	Sphericity Assumed	,007	60	,000		
	Greenhouse-Geisser	,007	58,257	,000		
	Huynh-Feldt	,007	60,000	,000		
	Lower-bound	,007	30,000	,000		

None of the above tests is statistically significant to influence the global efficiency of the individuals' brain network.

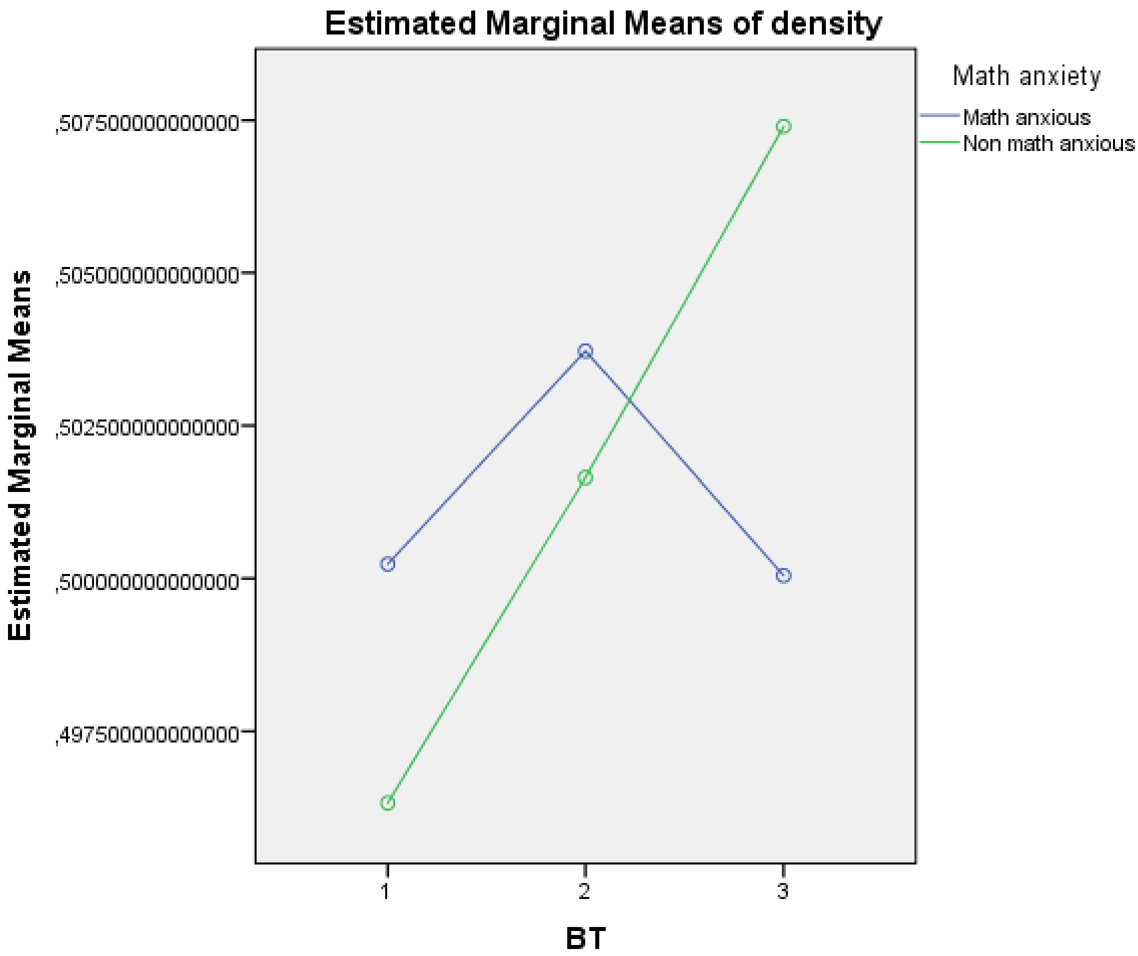
Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	24,150	1	24,150	394996,164	,000
MA1NMA2	4,982E-6	1	4,982E-6	,081	,777
Error	,002	30	6,114E-5		

From the graph below, we can deduce that the graph of math anxious individuals, is more dense as far as BT1 and BT2 is concerned, and there is a great increase in the density of the brain network of non math anxious ones as far as BT3 is concerned. The within subject test indicate that there is not a significant **Back test** effect. The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far.



Density Alpha 2

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,498491704374058	,010886927561158	16
	Non math anxious	,505090497737557	,008222171250760	16
	Total	,501791101055807	,010064777240318	32
BT2	Math anxious	,503723604826546	,016722069283658	16
	Non math anxious	,498821644042232	,010387798711241	16
	Total	,501272624434389	,013918244239636	32
BT3	Math anxious	,500659879336350	,013085062208979	16
	Non math anxious	,497501885369533	,007927375438027	16
	Total	,499080882352941	,010762412822141	32

Tests of Within-Subjects Effects

Measure: density

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	6,623E-5	,519	,598
	Greenhouse-Geisser	,000	1,981	6,688E-5	,519	,596
	Huynh-Feldt	,000	2,000	6,623E-5	,519	,598
	Lower-bound	,000	1,000	,000	,519	,477
BT * MA1NMA2	Sphericity Assumed	,001	2	,000	2,408	,099
	Greenhouse-Geisser	,001	1,981	,000	2,408	,099
	Huynh-Feldt	,001	2,000	,000	2,408	,099
	Lower-bound	,001	1,000	,001	2,408	,131
Error(BT)	Sphericity Assumed	,008	60	,000		
	Greenhouse-Geisser	,008	59,418	,000		
	Huynh-Feldt	,008	60,000	,000		
	Lower-bound	,008	30,000	,000		

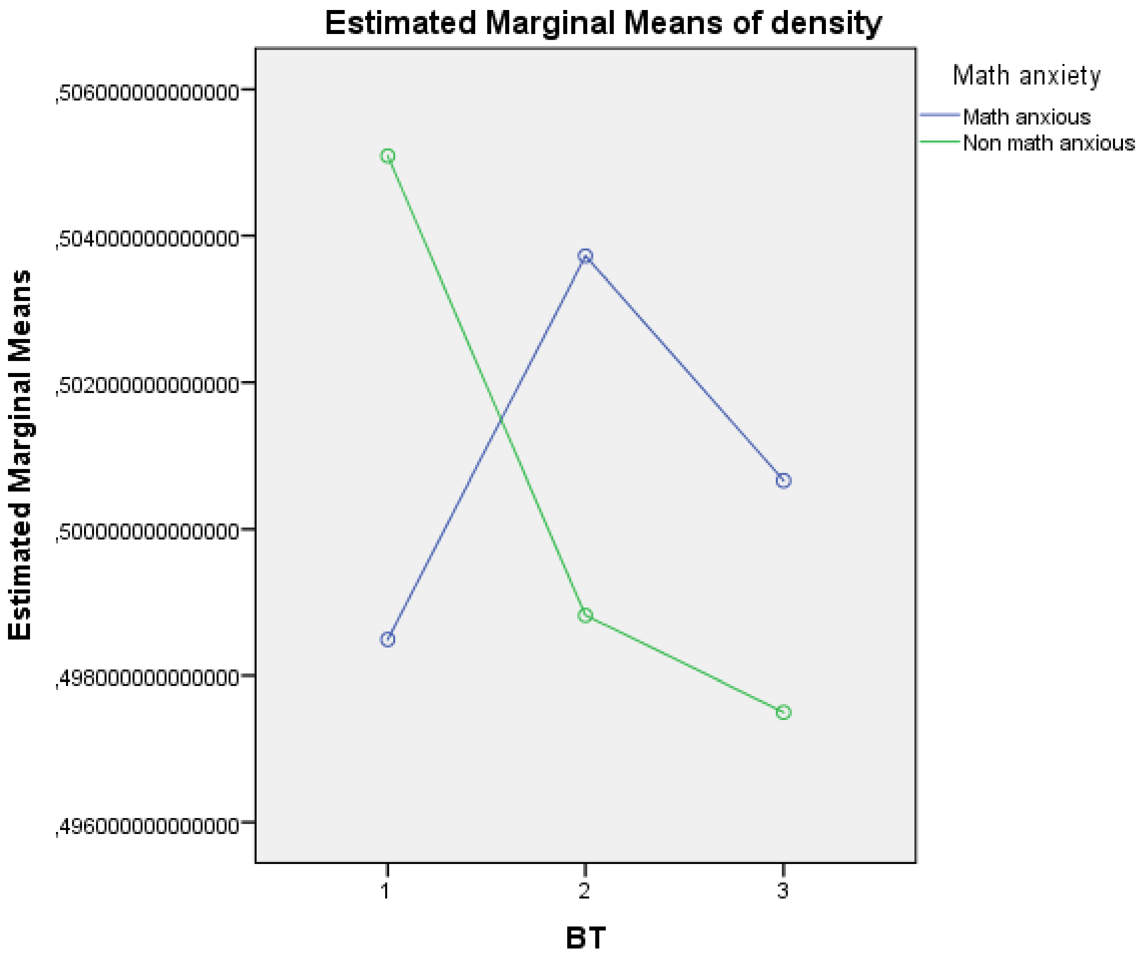
None of the interactions is statistically significant to influence the density of the individuals' brain network, so there is no need to analyze relevant statistical tests because they do not provide useful information.

Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	24,069	1	24,069	162003,977	,000
MA1NMA2	5,693E-6	1	5,693E-6	,038	,846
Error	,004	30	,000		



From the graph above, we can deduce that the network of math anxious individuals, has grater density in BT2 and BT3, and there is a great gap in the density of the brain network of non math anxious ones as far as BT1 is concerned. The within subject test indicate that there is not a significant **Back test** effect. The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far

Density betta

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,502733785822021	,009174087515483	16
	Non math anxious	,501743966817496	,017068235555962	16
	Total	,502238876319759	,013488544882337	32
BT2	Math anxious	,498020361990950	,013053149144603	16
	Non math anxious	,496229260935143	,013374877550924	16
	Total	,497124811463047	,013031902697387	32
BT3	Math anxious	,499575791855204	,012059980557061	16
	Non math anxious	,494061085972851	,013716025554588	16
	Total	,496818438914027	,013009776929620	32

Tests of Within-Subjects Effects

Measure: density

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,001	2	,000	1,447	,243
	Greenhouse-Geisser	,001	1,929	,000	1,447	,244
	Huynh-Feldt	,001	2,000	,000	1,447	,243
	Lower-bound	,001	1,000	,001	1,447	,238
BT * MA1NMA2	Sphericity Assumed	9,329E-5	2	4,664E-5	,228	,797
	Greenhouse-Geisser	9,329E-5	1,929	4,835E-5	,228	,789
	Huynh-Feldt	9,329E-5	2,000	4,664E-5	,228	,797
	Lower-bound	9,329E-5	1,000	9,329E-5	,228	,637
Error(BT)	Sphericity Assumed	,012	60	,000		
	Greenhouse-Geisser	,012	57,875	,000		
	Huynh-Feldt	,012	60,000	,000		
	Lower-bound	,012	30,000	,000		

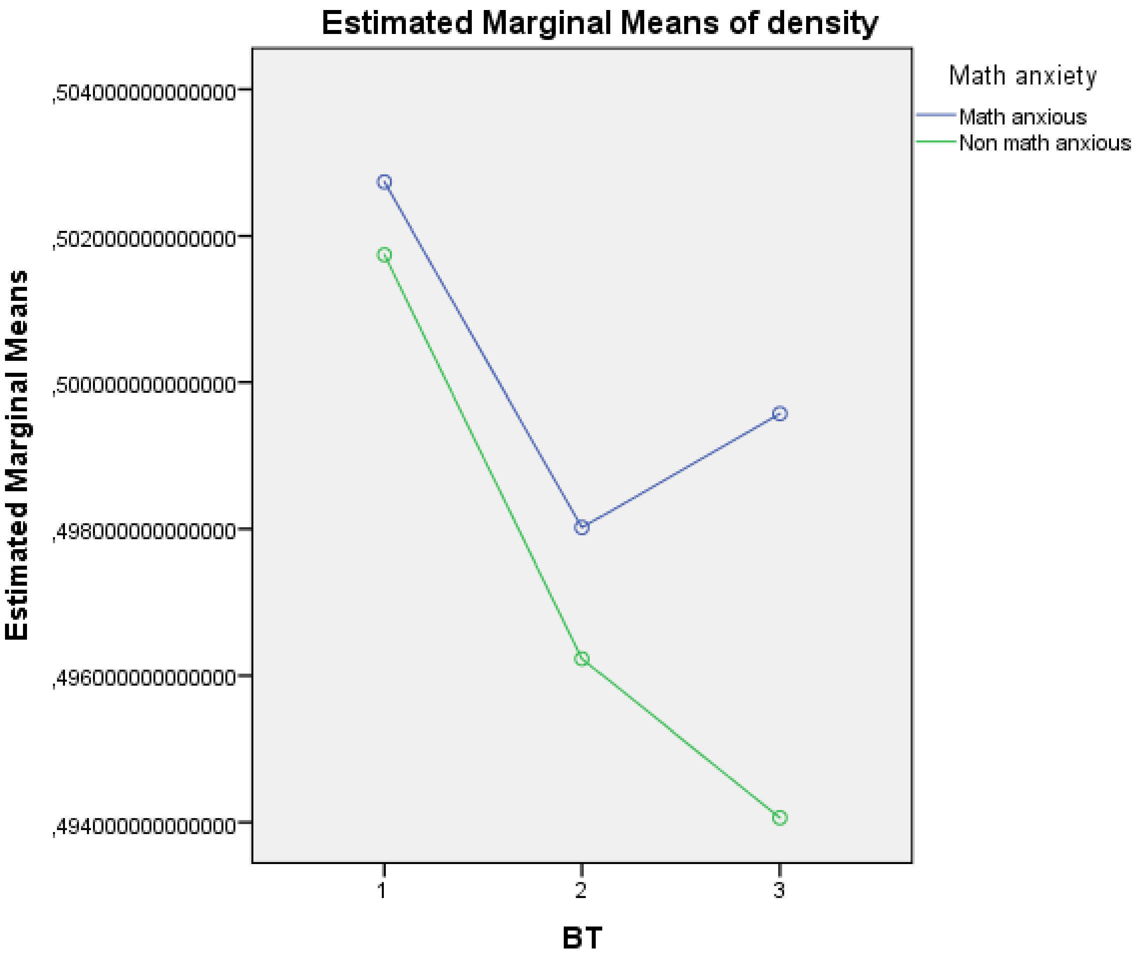
None of the interactions reaches statistical significance to influence the global efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	23,878	1	23,878	200434,582	,000
MA1NMA2	,000	1	,000	1,540	,224
Error	,004	30	,000		



From the graph above, we can deduce that the graph of math anxious individuals show greater density for the beta rhythm and for all three back tests, than the graph of the non math anxious ones. There is a great gap in the efficiency of the brain network of math anxious and non math anxious ones as far as BT3 is concerned. The within subject test indicate that there is not a significant **Back test** effect, and the interaction is not significant, too.The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far.

Density delta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,501084087481146	,009354549303127	16
	Non math anxious	,503063725490196	,004314435192140	16
	Total	,502073906485671	,007236067566314	32
BT2	Math anxious	,498067496229261	,009390957319315	16
	Non math anxious	,501979638009050	,007575964387089	16
	Total	,500023567119155	,008625204182634	32
BT3	Math anxious	,502215309200603	,007007050545227	16
	Non math anxious	,500377073906486	,007004513627700	16
	Total	,501296191553545	,006954836793457	32

Tests of Within-Subjects Effects

Measure: density

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	6,857E-5	2	3,428E-5	,533	,590
	Greenhouse-Geisser	6,857E-5	1,948	3,519E-5	,533	,585
	Huynh-Feldt	6,857E-5	2,000	3,428E-5	,533	,590
	Lower-bound	6,857E-5	1,000	6,857E-5	,533	,471
BT * MA1NMA2	Sphericity Assumed	,000	2	6,850E-5	1,065	,351
	Greenhouse-Geisser	,000	1,948	7,032E-5	1,065	,350
	Huynh-Feldt	,000	2,000	6,850E-5	1,065	,351
	Lower-bound	,000	1,000	,000	1,065	,310
Error(BT)	Sphericity Assumed	,004	60	6,430E-5		
	Greenhouse-Geisser	,004	58,452	6,601E-5		
	Huynh-Feldt	,004	60,000	6,430E-5		
	Lower-bound	,004	30,000	,000		

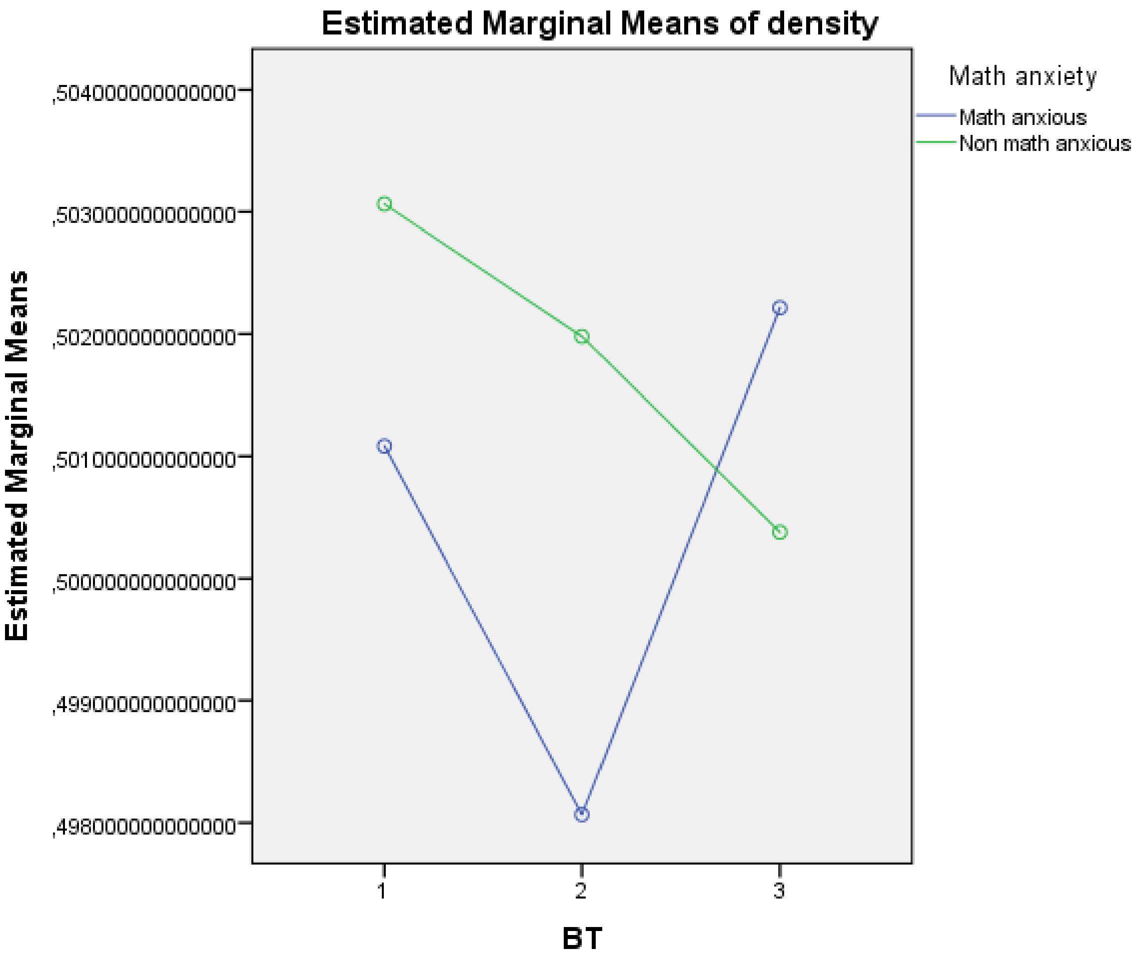
None of the tests above reaches statistical significance to influence the global efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	24,109	1	24,109	520412,715	,000
MA1NMA2	4,382E-5	1	4,382E-5	,946	,339
Error	,001	30	4,633E-5		



From the graph above, we can deduce that the network of non math anxious individuals show greater density for the delta rhythm and for the first and the second back tests, than the graph of the math anxious ones. There is a great gap in the density of the brain network of math anxious and non math anxious ones as far as BT2 is concerned. The within subject test indicate that there is not a significant **Back test** effect, and the interaction is not significant, too. The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far

Density gamma :

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,497454751131222	,005527274119368	16
	Non math anxious	,505938914027149	,014406328896709	16
	Total	,501696832579186	,011566420017166	32
BT2	Math anxious	,501319758672700	,013066576633824	16
	Non math anxious	,505326168929110	,012487827800024	16
	Total	,503322963800905	,012736320437011	32
BT3	Math anxious	,498680241327300	,012155590171016	16
	Non math anxious	,499764328808447	,013073013304484	16
	Total	,499222285067873	,012429585808255	32

Tests of Within-Subjects Effects

Measure: density

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	,000	1,037	,361
	Greenhouse-Geisser	,000	1,939	,000	1,037	,359
	Huynh-Feldt	,000	2,000	,000	1,037	,361
	Lower-bound	,000	1,000	,000	1,037	,317
BT * MA1NMA2	Sphericity Assumed	,000	2	,000	,845	,435
	Greenhouse-Geisser	,000	1,939	,000	,845	,432
	Huynh-Feldt	,000	2,000	,000	,845	,435
	Lower-bound	,000	1,000	,000	,845	,365
Error(BT)	Sphericity Assumed	,008	60	,000		
	Greenhouse-Geisser	,008	58,157	,000		
	Huynh-Feldt	,008	60,000	,000		
	Lower-bound	,008	30,000	,000		

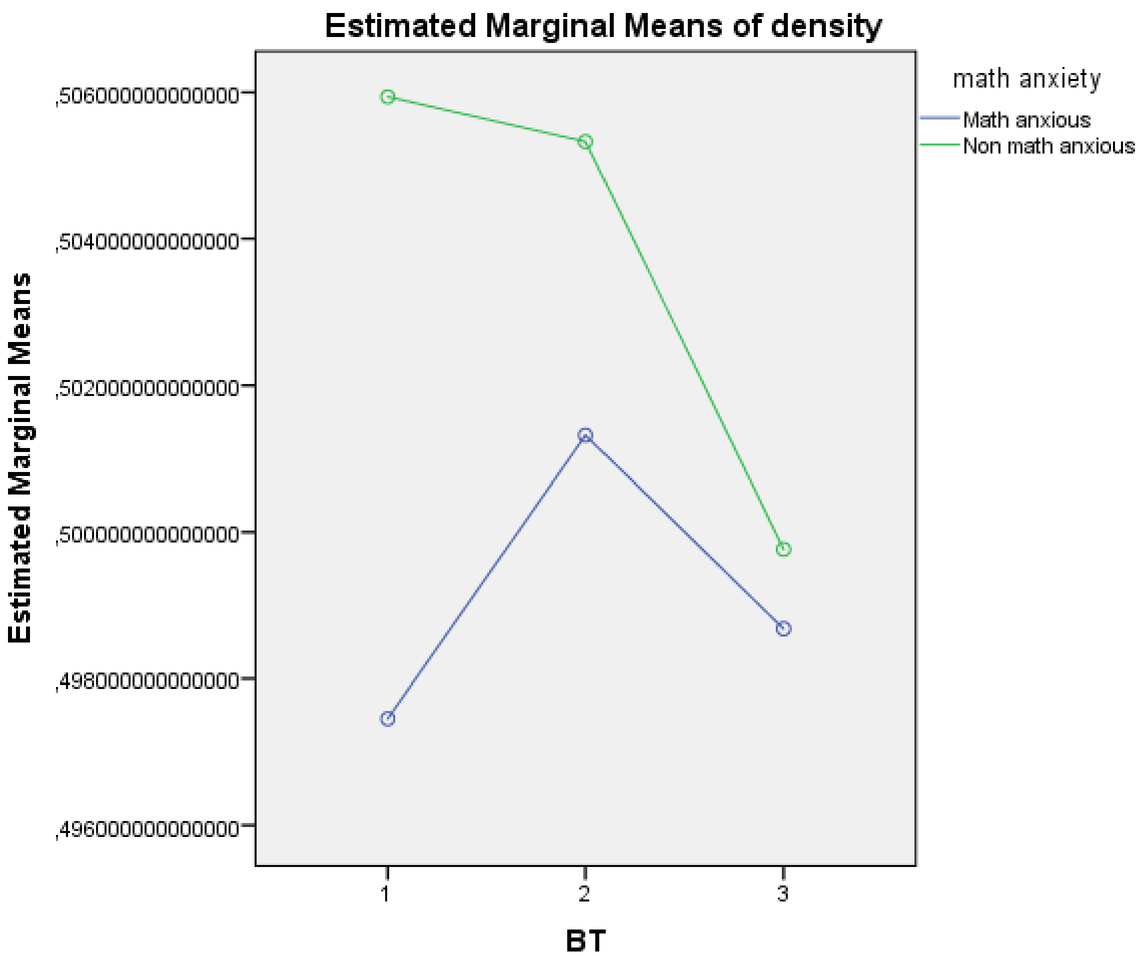
None of the above tests reaches statistical significance to influence the global efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	24,136	1	24,136	135106,307	,000
MA1NMA2	,000	1	,000	2,751	,108
Error	,005	30	,000		



From the graph above, we can deduce that the network of non math anxious individuals show greater density for the gamma rhythm for all three back tests, than math anxious ones. There is a great gap in the density of the brain network of math anxious and non math anxious ones especially when referring to BT1. The within subject test indicate that there is not a significant **Back test** effect, and the interaction is not significant, too. The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far.

Density theta :

Descriptive Statistics

	math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,501743966817496	,011672554066489	16
	non math anxious	,499104449472097	,008312605457817	16
	Total	,500424208144796	,010057825285238	32
BT2	math anxious	,506457390648567	,010129073605701	16
	non math anxious	,492788461538462	,014816573654018	16
	Total	,499622926093514	,014285851096911	32
BT3	math anxious	,49952865744	,012690838642	16
	non math anxious	,50758861256	,016403870787	16
	Total	,50355863500	,014996632360	32

Tests of Within-Subjects Effects

Measure: density

Mauchly's Test of Sphericity[a]

Measure: density

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	Df	Sig.	Epsilon[b]		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
BT	,807	6,236	2	,044	,838	,911	,500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

From Mauchy's test of sphericity, we can see that sphericity is violated (p=0,44), so we use the Greenhouse-Geisser correction row, and the mean scores are statistically significantly different (p<0,0005)

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	,000	1,008	,371
	Greenhouse-Geisser	,000	1,676	,000	1,008	,360
	Huynh-Feldt	,000	1,823	,000	1,008	,365
	Lower-bound	,000	1,000	,000	1,008	,323
BT * MA1NMA2	Sphericity Assumed	,002	2	,001	6,876	,002
	Greenhouse-Geisser	,002	1,676	,001	6,876	,004
	Huynh-Feldt	,002	1,823	,001	6,876	,003
	Lower-bound	,002	1,000	,002	6,876	,014
Error(BT)	Sphericity Assumed	,008	60	,000		
	Greenhouse-Geisser	,008	50,272	,000		
	Huynh-Feldt	,008	54,678	,000		
	Lower-bound	,008	30,000	,000		

Looking at Greenhouse-Geisser row of data, we can see that the interactions are not statistically significant as p should be less than 0,0005.

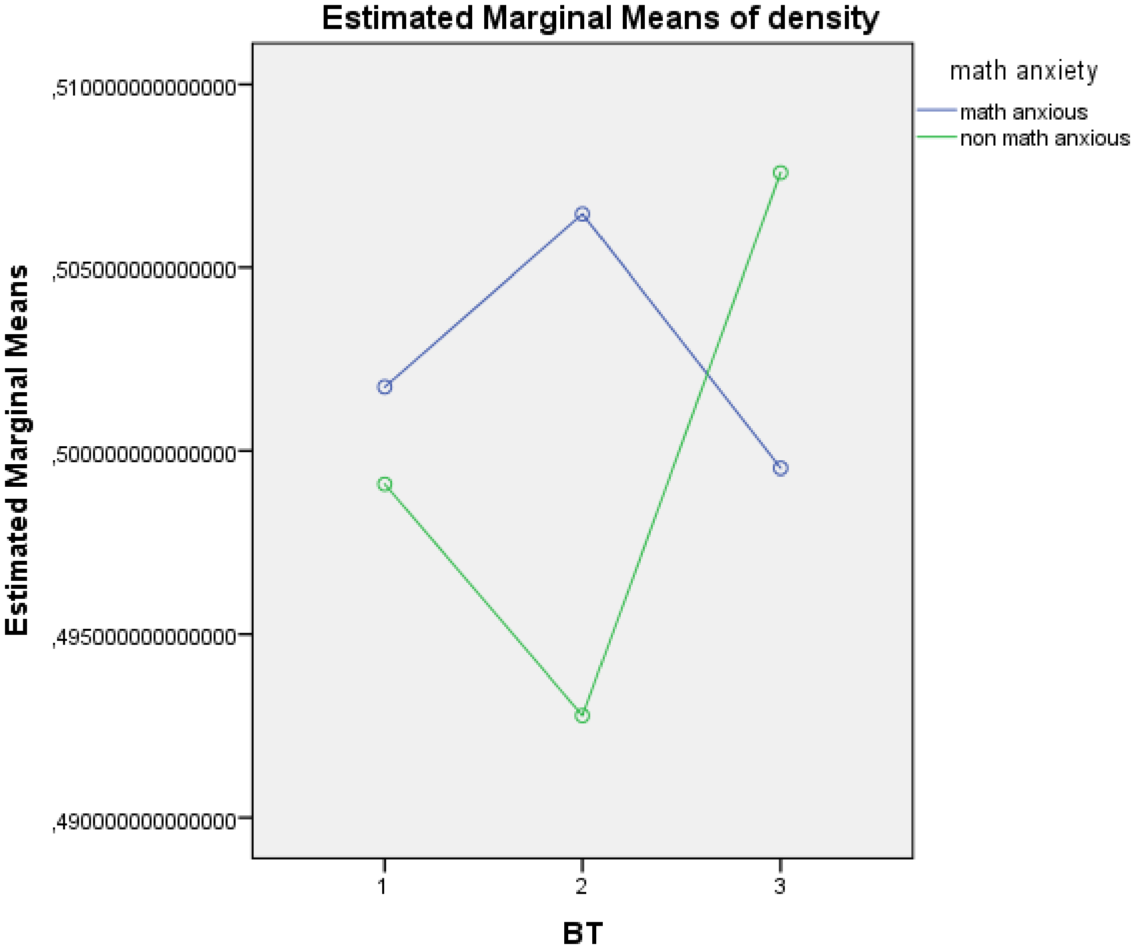
Tests of Between-Subjects Effects

Measure: density

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	24,116	1	24,116	118138,363	,000
MA1NMA2	,000	1	,000	,889	,353
Error	,006	30	,000		

From the graph below, we can deduce that the network of math anxious individuals has greater density for the theta rhythm for the first and the second back tests, than math anxious ones. There is a great gap in the density of the brain network of math anxious and non math anxious ones especially when referring to BT2. The within subject test indicate that there is not a significant **Back test** effect, and the interaction is not significant, too. The variable group is not significant as indicated from the between subjects effects, and that is the reason why the two lines are not very far.



Average local efficiency :

Alpha1 :

Descriptive Statistics

	MATH ANXIETY	Mean	Std. Deviation	N
BT1	Math anxious MA	,678847130490815	,016957242089620	16
	Non math anxious NMA	,686959934221036	,026845706346097	16
	Total	,682903532355925	,022712106524709	32
BT2	Math anxious MA	,680355200026533	,012289330585679	16
	Non math anxious NMA	,684979399983397	,023792189495984	16
	Total	,682667300004965	,018985905898331	32
BT3	Math anxious MA	,678967026750371	,014030216193602	16
	Non math anxious NMA	,675188904021393	,022099152857289	16
	Total	,677077965385882	,018517198825447	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,002	2	,001	3,013	,051
	Greenhouse-Geisser	,002	1,966	,001	3,013	,052
	Huynh-Feldt	,002	2,000	,001	3,013	,051
	Lower-bound	,002	1,000	,002	3,013	,086
BT * MATHANXIETY	Sphericity Assumed	,002	2	,001	2,588	,078
	Greenhouse-Geisser	,002	1,966	,001	2,588	,079
	Huynh-Feldt	,002	2,000	,001	2,588	,078
	Lower-bound	,002	1,000	,002	2,588	,111
Error(BT)	Sphericity Assumed	,077	204	,000		
	Greenhouse-Geisser	,077	200,495	,000		
	Huynh-Feldt	,077	204,000	,000		
	Lower-bound	,077	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204)= 3,013 is marginally significant at 0,051, almost 0,05. This means that ignoring whether participants are math anxious or non math anxious, there is an overall marginally significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,002	1	,002	4,258	,042
	Quadratic	,000	1	,000	1,477	,227
BT * MATHANXIETY	Linear	,002	1	,002	4,435	,038
	Quadratic	,000	1	,000	,311	,578
Error(BT)	Linear	,042	102	,000		
	Quadratic	,034	102	,000		

From the above table it is clear that we have a statistically significant linear component for Back test, so we can deduce that average local efficiency is changing linearly as Back tests are getting more difficult.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	144,644	1	144,644	318156,457	,000
MATHANXIETY	,001	1	,001	1,530	,219
Error	,046	102	,000		

We have a non significant effect for math anxiety.

Pairwise Comparisons

Measure: Average local efficiency

(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1	2	,000	,003	1,000	-,006	,007
	3	,006	,003	,125	-,001	,013
2	1	,000	,003	1,000	-,007	,006
	3	,006	,003	,086	-,001	,012
3	1	-,006	,003	,125	-,013	,001
	2	-,006	,003	,086	-,012	,001

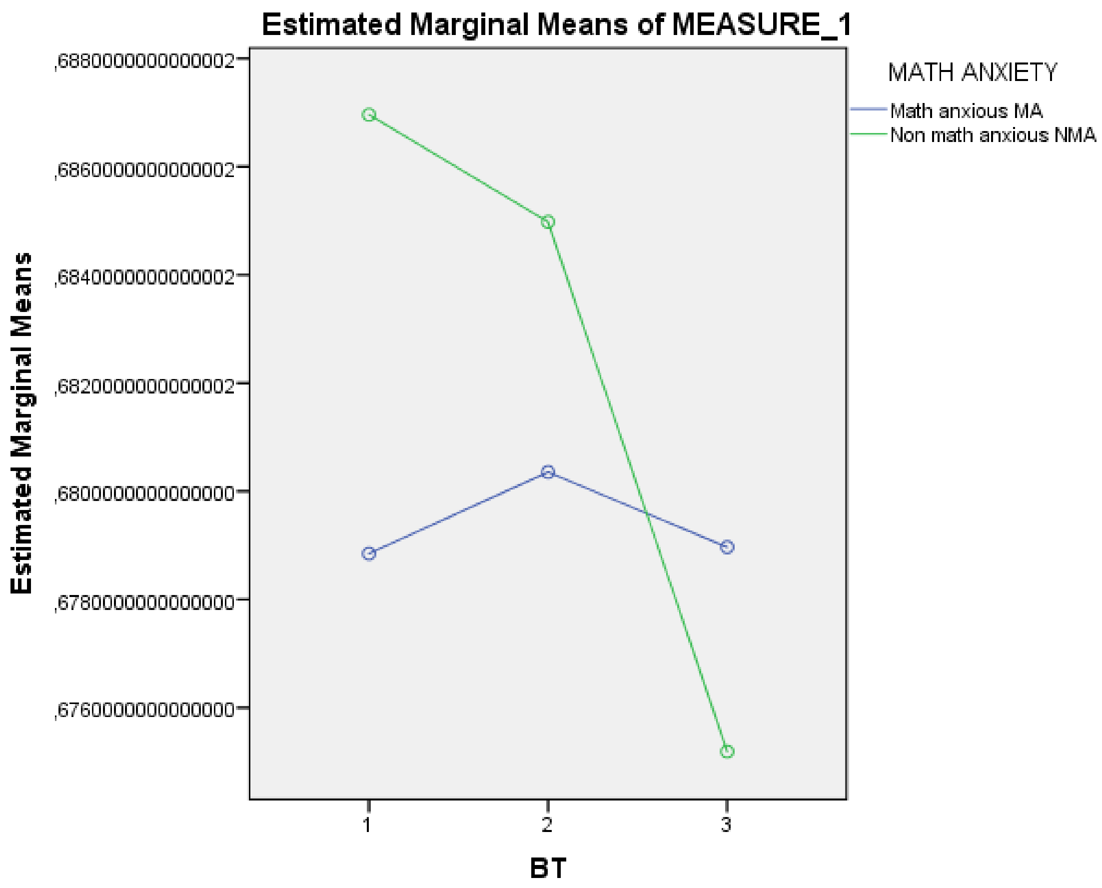
Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

The Bonferroni pairwise comparisons in the table above are equal to independent t-tests. Speciffically, if you divide the Mean Difference by the Standard Error of the Difference, you will get exactly the *t* values you would have if you ran a t-test for the mean of each pair.

We can see that we do not have a statistically significant result in our pairwise comparisons.

From the graph below, we can deduce that the network of non math anxious individuals has greater average local efficiency for the alpha rhythm for the first and the second back tests, than math anxious ones, when in the third back test math anxious individuals out-performed non math anxious ones as far as local efficiency is concerned. The within subject test indicate that there is a significant **Back test** effect, whereas the interaction does not reach a convenient level of significance. The variable group is not significant as indicated from the between subjects contrasts, and that is the reason why the two lines are not very far.



Alpha 2 :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,677313362024278	,016576299101397	16
	Non math anxious	,692727435906417	,023667343264934	16
	Total	,685020398965348	,021757309629832	32
BT2	Math anxious	,689330157759213	,012973726614958	16
	Non math anxious	,694141713609022	,025415046446375	16
	Total	,691735935684118	,020224055269209	32
BT3	Math anxious	,677847849447941	,017217673096823	16
	Non math anxious	,683582952297254	,019797925547881	16
	Total	,680715400872597	,018685929701740	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,006	2	,003	9,759	,000
	Greenhouse-Geisser	,006	1,964	,003	9,759	,000
	Huynh-Feldt	,006	2,000	,003	9,759	,000
	Lower-bound	,006	1,000	,006	9,759	,002
BT * Mathanxiety	Sphericity Assumed	,002	2	,001	2,728	,068
	Greenhouse-Geisser	,002	1,964	,001	2,728	,069
	Huynh-Feldt	,002	2,000	,001	2,728	,068
	Lower-bound	,002	1,000	,002	2,728	,102
Error(BT)	Sphericity Assumed	,067	204	,000		
	Greenhouse-Geisser	,067	200,313	,000		
	Huynh-Feldt	,067	204,000	,000		
	Lower-bound	,067	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204)= 9,759 is significant at 0,000. This means that ignoring whether participants are math anxious or non math anxious, there is an overall significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,001	1	,001	2,759	,100
	Quadratic	,005	1	,005	17,695	,000
BT * Mathanxiety	Linear	,001	1	,001	3,486	,065
	Quadratic	,001	1	,001	1,868	,175
Error(BT)	Linear	,036	102	,000		
	Quadratic	,031	102	,000		

From the above table it is clear that we have a statistically significant linear component for Back test, so we can deduce that average local efficiency is changing linearly as Back tests are getting more difficult.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	146,751	1	146,751	287010,714	,000
Mathanxiety	,006	1	,006	11,424	,001
Error	,052	102	,001		

The table above, demonstrates that the effect for the "group" (effect of math anxiety) is significant.

airwise Comparisons

Measure: Average local efficiency

(I) Math anxiety	(J) Math anxiety	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	Upper Bound
Math anxious	Non math anxious	-,009*	,003	,001	-,014	-,004
Non math anxious	Math anxious	,009*	,003	,001	,004	,014

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.
b. Adjustment for multiple comparisons: Bonferroni.

The Bonferroni pairwise comparisons in the table above are equal to independent t-tests. We can see that there is a statistically significant difference between Math anxious and non math anxious individuals.

Pairwise Comparisons

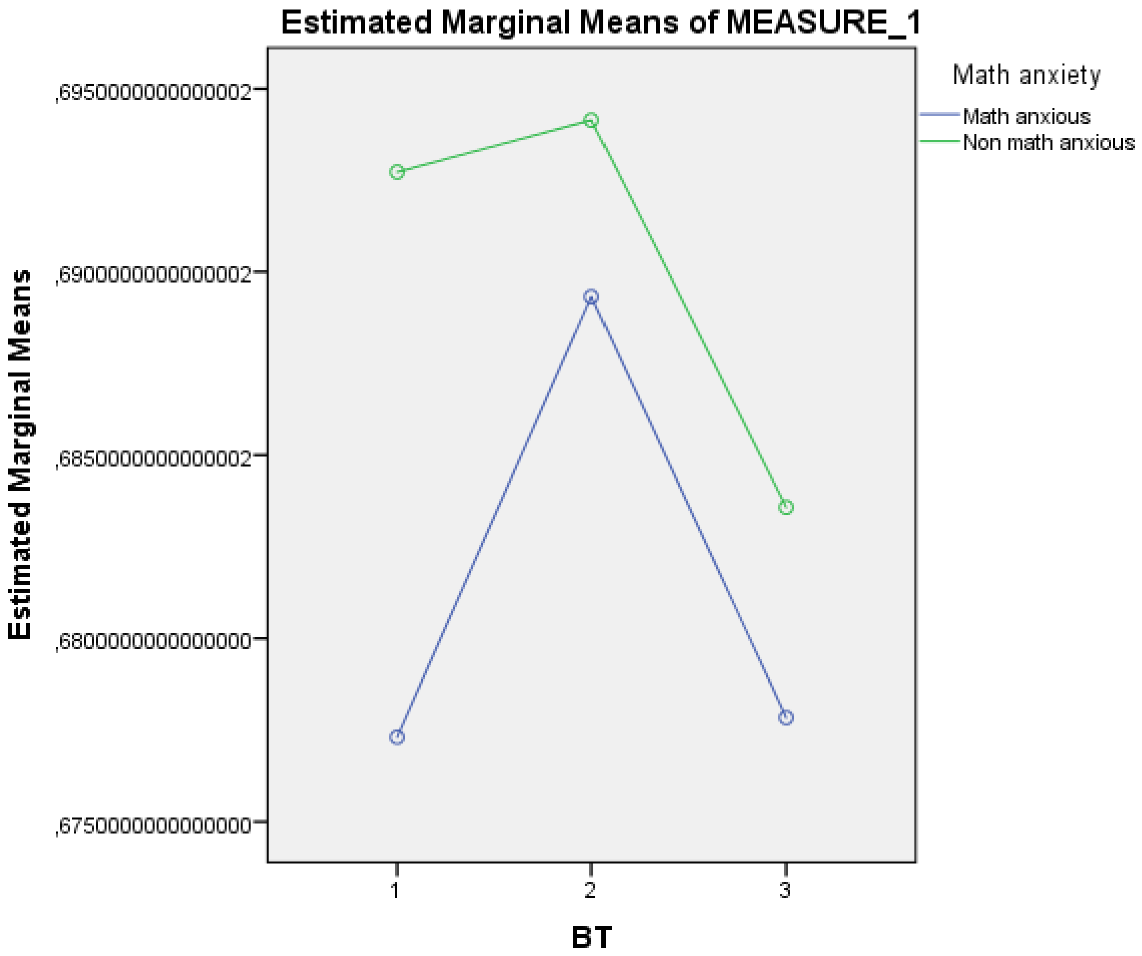
Measure: Average local efficiency

(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-,007*	,002	,015	-,012	-,001
	3	,004	,003	,299	-,002	,011
2	1	,007*	,002	,015	,001	,012
	3	,011*	,003	,000	,005	,017
3	1	-,004	,003	,299	-,011	,002
	2	-,011*	,003	,000	-,017	-,005

Based on estimated marginal means
*. The mean difference is significant at the ,05 level.
b. Adjustment for multiple comparisons: Bonferroni.

From the table above, which is designed based on Bonferroni intervals, we can deduce that the differences appear between pairs Back test 1 - Back test 2 and Back test 2 - Back test 3.

The between groups test indicates that there the variable **group (math anxiety)** is significant, consequently in the graph we see that the lines for the two groups are rather far apart. The within subject test indicate that there is a significant **back test** effect, in other words, the groups do change over the back tests, both groups are getting more efficient locally on average from BT1 to BT2, and less efficient from BT2 to BT3. Moreover, the interaction of **back test** and **group** is not significant which means that the groups are changing over the back tests in a same way, which means that in the graph the lines will almost be parallel.



Betta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	math anxious	,676133138811009	,019100792315265	16
	non math anxious	,683608362786206	,023660443523176	16
	Total	,679870750798608	,021724299156238	32
BT2	math anxious	,687899308563927	,015795667055813	16
	non math anxious	,674342590698899	,020037618744719	16
	Total	,681120949631413	,019202516010970	132
BT3	math anxious	,680354397862655	,016383179519660	16
	non math anxious	,679641536556711	,023091925666300	16
	Total	,679997967209683	,019926354252743	32

Sphericity is not violated, so we take the values for sphericity assumed (first row without corrections). In the table below, we can see that F (2, 204)= 7,518 is significant at 0,001. This means that there is a significant interaction between the two independent variables: target group (math anxiety) and Back test.

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	9,846E-5	2	4,923E-5	,127	,881
	Greenhouse-Geisser	9,846E-5	1,986	4,958E-5	,127	,880
	Huynh-Feldt	9,846E-5	2,000	4,923E-5	,127	,881
	Lower-bound	9,846E-5	1,000	9,846E-5	,127	,723
BT * Mathanxiety	Sphericity Assumed	,006	2	,003	7,518	,001
	Greenhouse-Geisser	,006	1,986	,003	7,518	,001
	Huynh-Feldt	,006	2,000	,003	7,518	,001
	Lower-bound	,006	1,000	,006	7,518	,007
Error(BT)	Sphericity Assumed	,079	204	,000		
	Greenhouse-Geisser	,079	202,579	,000		
	Huynh-Feldt	,079	204,000	,000		
	Lower-bound	,079	102,000	,001		

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	8,416E-7	1	8,416E-7	,002	,964
	Quadratic	9,762E-5	1	9,762E-5	,273	,602
BT * Mathanxiety	Linear	,001	1	,001	2,075	,153
	Quadratic	,005	1	,005	13,914	,000
Error(BT)	Linear	,043	102	,000		
	Quadratic	,036	102	,000		

We can see that the quadratic component of the interaction is statistically significant, reflecting the fact that the increase/decrease levels off, and even falls, at the last measurement.

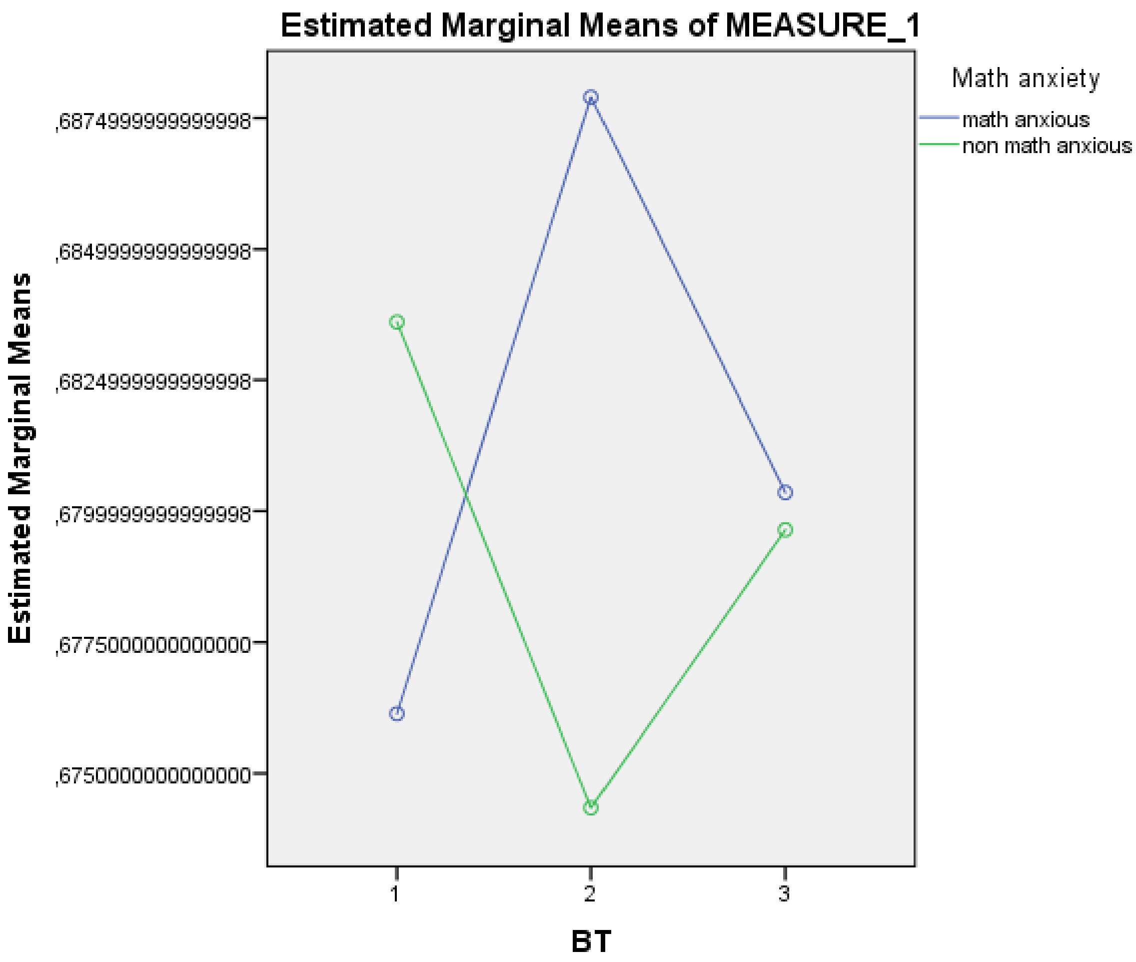
Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	144,409	1	144,409	351155,635	,000
Mathanxiety	,000	1	,000	,973	,326
Error	,042	102	,000		

The effect of the group (math anxiety) is not statistically significant according to the table above.



The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups are not generally far apart. The within subject test indicate that there is not a significant **back test** effect. Moreover, the interaction of **back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel. In the graph we see that the groups have non-parallel lines and they have a great gap as far as Back test 2 is concerned, as implied from the quadratic component of the interaction.

Delta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,677298716885079	,013638915711303	16
	Non math anxious	,673248222354743	,023912672881491	16
	Total	,675273469619911	,019477695086627	32
BT2	Math anxious	,684858256681881	,016235869791716	16
	Non math anxious	,674187832611482	,023280484299577	16
	Total	,679523044646682	,020679033978872	32
BT3	Math anxious	,682763718219719	,015556775589770	16
	Non math anxious	,678436258623113	,025394297710447	16
	Total	,680599988421416	,021068073748442	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	Df	Mean Square	F	Sig.
BT	Sphericity Assumed	,002	2	,001	2,268	,106
	Greenhouse-Geisser	,002	1,966	,001	2,268	,107
	Huynh-Feldt	,002	2,000	,001	2,268	,106
	Lower-bound	,002	1,000	,002	2,268	,135
BT * Mathanxiety	Sphericity Assumed	,001	2	,000	1,002	,369
	Greenhouse-Geisser	,001	1,966	,000	1,002	,368
	Huynh-Feldt	,001	2,000	,000	1,002	,369
	Lower-bound	,001	1,000	,001	1,002	,319
Error(BT)	Sphericity Assumed	,074	204	,000		
	Greenhouse-Geisser	,074	200,563	,000		
	Huynh-Feldt	,074	204,000	,000		
	Lower-bound	,074	102,000	,001		

None of the above tests is statistically significant to influence the average local efficiency of the individuals' brain network.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	143,618	1	143,618	288637,826	,000
Mathanxiety	,003	1	,003	6,320	,014
Error	,051	102	,000		

The effect of the group (math anxiety) is statistically significant with $F(1, 102)=6{,}320$ being significant at $p = 0{,}014$.

Pairwise Comparisons

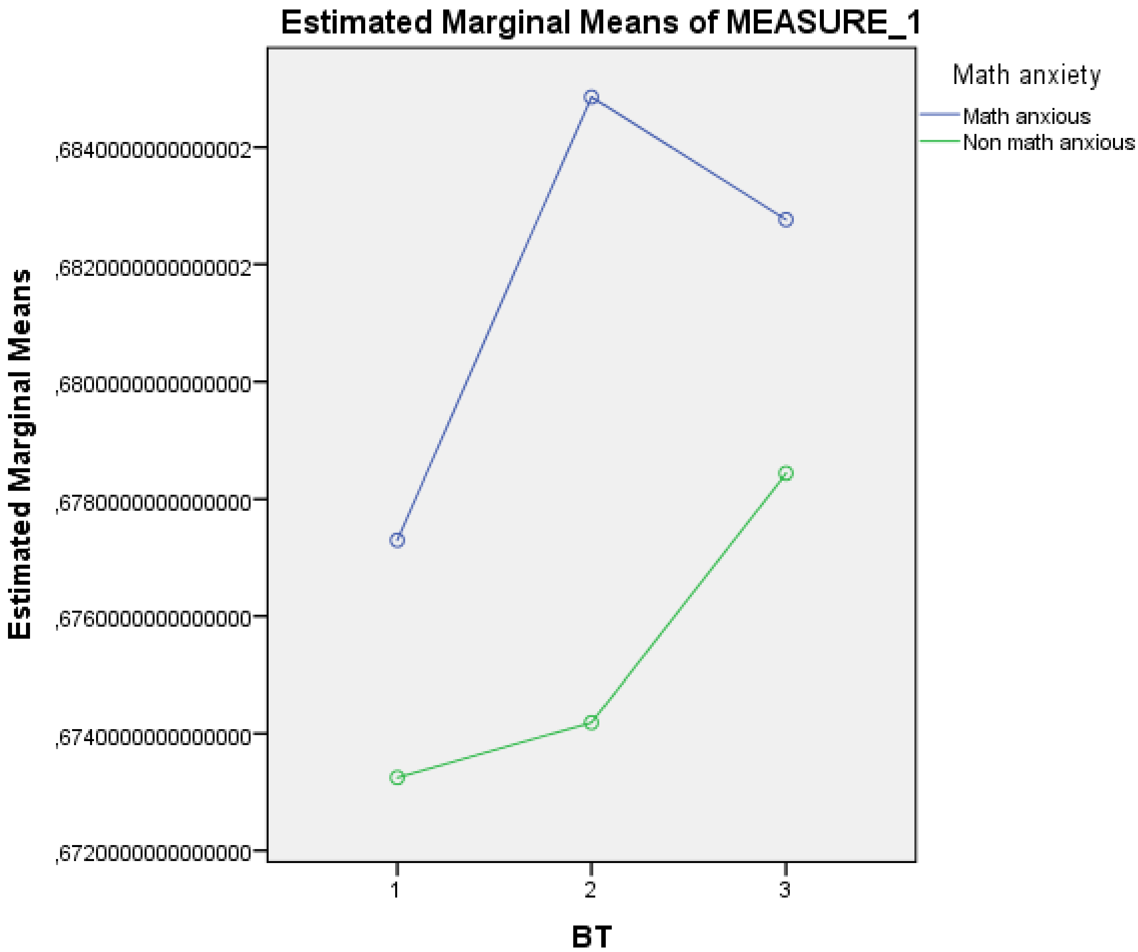
Measure: Average local efficiency

(I) Math anxiety	(J) Math anxiety	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
Math anxious	Non math anxious	,006*	,003	,014	,001	,011
Non math anxious	Math anxious	-,006*	,003	,014	-,011	-,001

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.



The between groups test indicates that there the variable **group (math anxiety)** is significant, consequently in the graph we see that the lines for the two groups are rather far apart. The within subject test indicate that there is not a significant **back test** effect, in other words, the groups do not change significantly locally in efficiency over back tests. In addition, since the lines are parallel, we are not surprised that there is no interaction.

Gamma :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,683931402124997	,013855092881164	52
	Non math anxious	,676400347965257	,023806035596884	52
	Total	,680165875045127	,019747894960832	104
BT2	Math anxious	,684489104750677	,017714616578335	52
	Non math anxious	,678659249694734	,020790620236685	52
	Total	,681574177222706	,019441872913800	104
BT3	Math anxious	,676744653396495	,014222207026897	52
	Non math anxious	,684186285201805	,022468843691601	52
	Total	,680465469299150	,019081570066606	104

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,000	2	5,724E-5	,179	,836
	Greenhouse-Geisser	,000	1,938	5,907E-5	,179	,830
	Huynh-Feldt	,000	1,994	5,741E-5	,179	,836
	Lower-bound	,000	1,000	,000	,179	,673
BT * Mathanxiety	Sphericity Assumed	,003	2	,002	5,455	,005
	Greenhouse-Geisser	,003	1,938	,002	5,455	,005
	Huynh-Feldt	,003	1,994	,002	5,455	,005
	Lower-bound	,003	1,000	,003	5,455	,021
Error(BT)	Sphericity Assumed	,065	204	,000		
	Greenhouse-Geisser	,065	197,671	,000		
	Huynh-Feldt	,065	203,412	,000		
	Lower-bound	,065	102,000	,001		

Sphericity is not violated, so we take the values for sphericity assumed (first row without corrections). We can see that F (2, 204)= 5,455 is significant at 0,005. This means that there is a significant interaction between the two independent variables: target group (math anxiety) and Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	4,667E-6	1	4,667E-6	,013	,911
	Quadratic	,000	1	,000	,406	,525
BT * Mathanxiety	Linear	,003	1	,003	7,869	,006
	Quadratic	,001	1	,001	2,147	,146
Error(BT)	Linear	,038	102	,000		
	Quadratic	,028	102	,000		

According to the above table there is a linear component of the interaction of Back test and Math anxiety, meaning that average local efficiency increases/ decreases linearly over the back tests.

Tests of Between-Subjects Effects

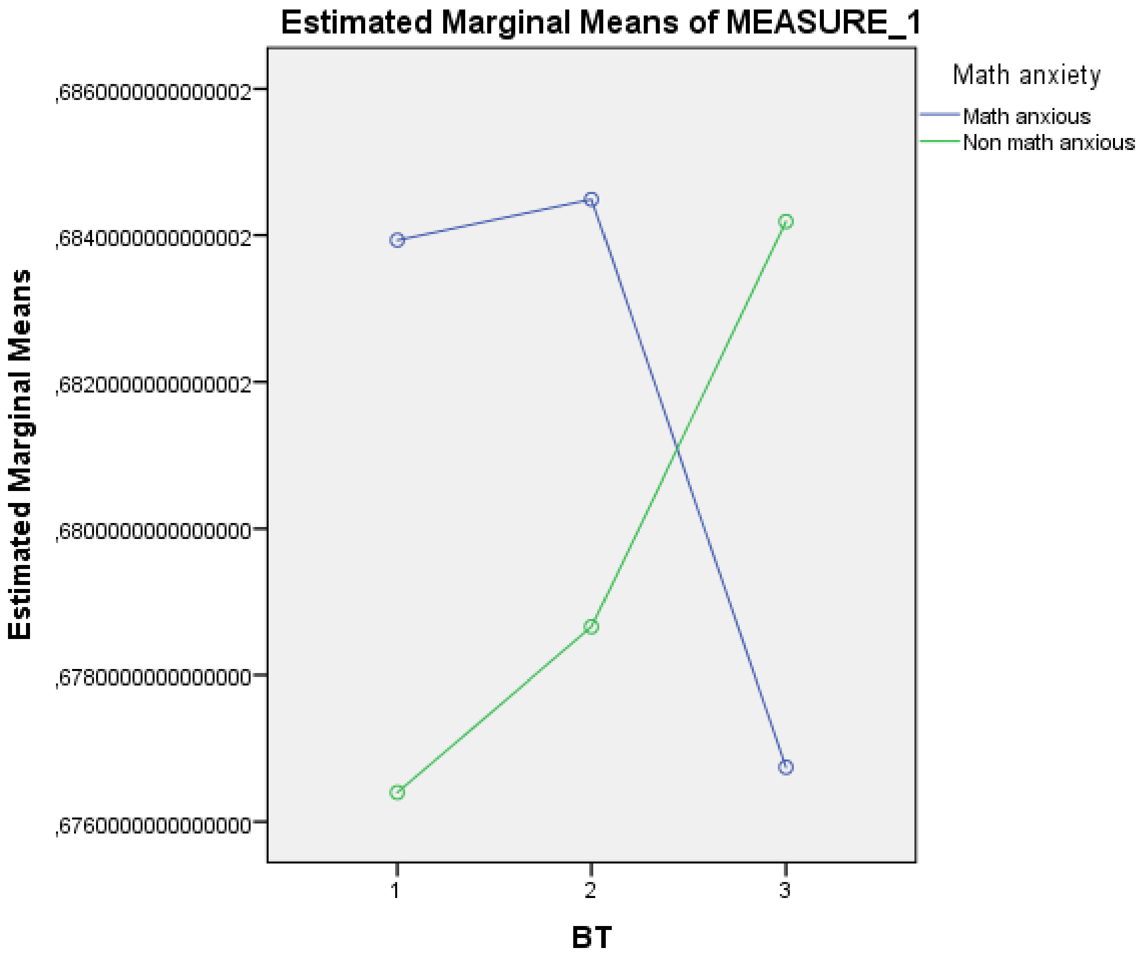
Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Intercept	144,581	1	144,581	310684,503	,000
Mathanxiety	,000	1	,000	,653	,421
Error	,047	102	,000		

The table above shows that the effect of the Group (math anxiety) is not statistically significant.

The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups are not generally far apart. The within subject test indicate that there is not a significant **back test** effect. Moreover, the interaction of **back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel. In the graph we see that the groups have non-parallel lines and they have a great gaps.



Theta :

Descriptive Statistics

	Math anxiety	Mean	Std. Deviation	N
BT1	Math anxious	,681665980807798	,013549381795320	16
	Non math anxious	,681719614307776	,024788571174877	16
	Total	,681692797557787	,019878535087617	32
BT2	Math anxious	,677230894498881	,013376279641768	16
	Non math anxious	,674556155072340	,025153497648924	16
	Total	,675893524785611	,020091730984808	32
BT3	Math anxious	,678174615914236	,015394717516099	16
	Non math anxious	,688794972805323	,017374074438545	16
	Total	,683484794359779	,017183825309254	32

Tests of Within-Subjects Effects

Measure: Average local efficiency

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Sphericity Assumed	,003	2	,002	4,495	,012
	Greenhouse-Geisser	,003	1,945	,002	4,495	,013
	Huynh-Feldt	,003	2,000	,002	4,495	,012
	Lower-bound	,003	1,000	,003	4,495	,036
BT * Mathanxiety	Sphericity Assumed	,003	2	,001	3,520	,031
	Greenhouse-Geisser	,003	1,945	,001	3,520	,033
	Huynh-Feldt	,003	2,000	,001	3,520	,031
	Lower-bound	,003	1,000	,003	3,520	,064
Error(BT)	Sphericity Assumed	,074	204	,000		
	Greenhouse-Geisser	,074	198,366	,000		
	Huynh-Feldt	,074	204,000	,000		
	Lower-bound	,074	102,000	,001		

Sphericity assumption is not violated, so we take the values of the first row without corrections. F (2, 204) = 4,495 for Back test, is significant at p = 0,012. This means that ignoring whether participants are math anxious or non math anxious, there is an overall significant difference in average local efficiency, proportional to back test difficulty. This is refered to as a "main effect" for Back test. Additionally, F (2, 204) = 3,520 is significant at p = 0.031, which means that there is an overall significant interaction between the two independent variables target group and Back test.

Tests of Within-Subjects Contrasts

Measure: Average local efficiency

Source	BT	Type III Sum of Squares	df	Mean Square	F	Sig.
BT	Linear	,000	1	,000	,517	,474
	Quadratic	,003	1	,003	7,668	,007
BT * Mathanxiety	Linear	,001	1	,001	4,491	,036
	Quadratic	,001	1	,001	2,745	,101
Error(BT)	Linear	,033	102	,000		
	Quadratic	,041	102	,000		

As far as Back test is concerned, it has a statistically significant quadratic component with F(1,102) = 7,668 being significant at p=0,007, reflecting the fact that the increase levels off, and even falls, at the last measurement. There is, also, a statistically significant linear component for the interaction with F(1,102) = 4,491 being significant at p = 0,036.

Tests of Between-Subjects Effects

Measure: Average local efficiency

Transformed Variable: Average

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.
Intercept	144,420	1	144,420	417696,294	,000
Mathanxiety	,001	1	,001	1,604	,208
Error	,035	102	,000		

Table of Between-subjects effects indicates that the variable group is not statistically significant.

Pairwise Comparisons

Measure: Average local efficiency

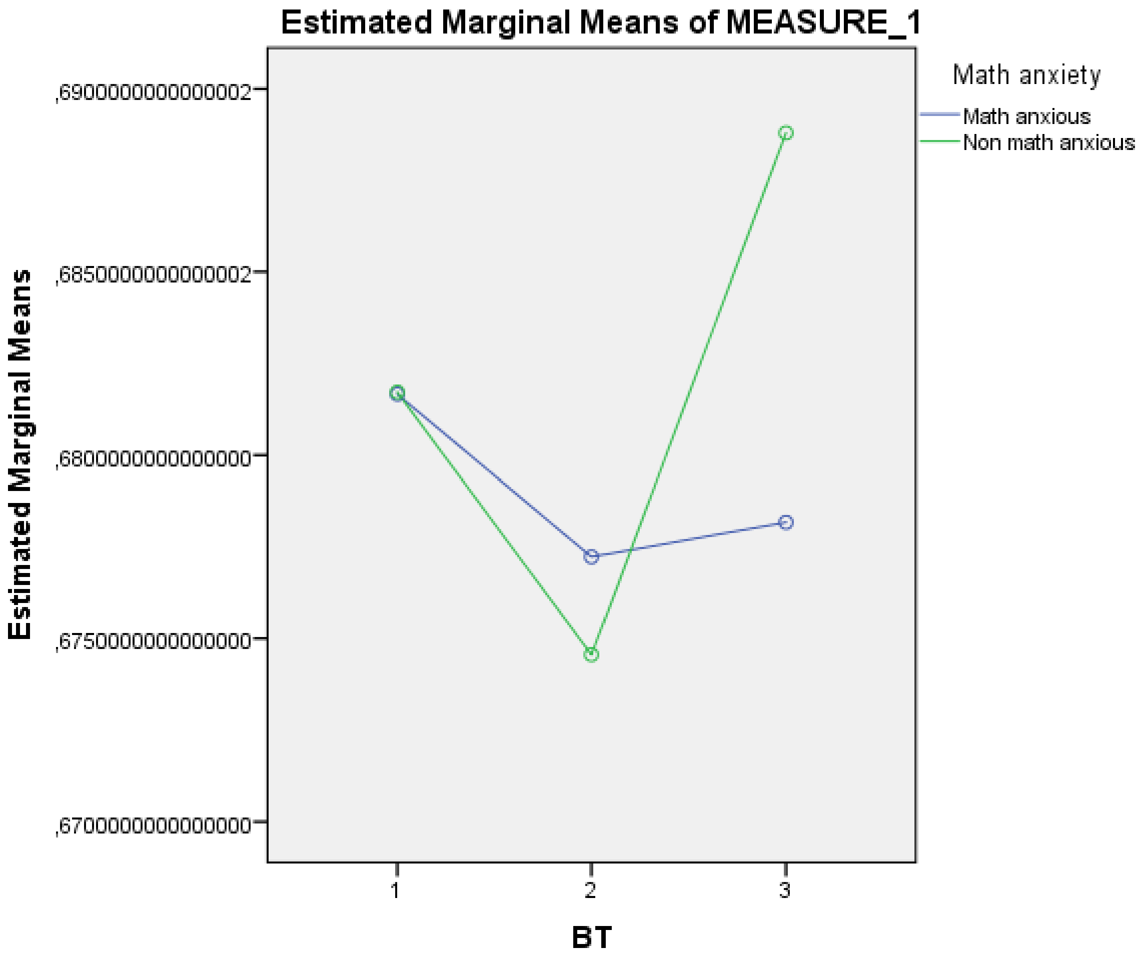
(I) BT	(J) BT	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	,006	,003	,135	-,001	,013
	3	-,002	,002	1,000	-,008	,004
2	1	-,006	,003	,135	-,013	,001
	3	-,008*	,003	,012	-,014	-,001
3	1	,002	,002	1,000	-,004	,008
	2	,008*	,003	,012	,001	,014

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Post hoc tests with Bonferroni correction showed that the differentiation is found in the pair BT2-BT3, being statistically significant at p=0,0



The between groups test indicates that there the variable **group** is not significant, consequently in the graph we see that the lines for the two groups are not far apart. The within subject test indicate that there is a significant **Back test** effect, in other words, the groups do change over back tests.. Moreover, the interaction of **back test** and **group** is significant which means that the groups are changing over back tests but are changing in different ways, which means that in the graph the lines will not be parallel.

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