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When the brain comes into play: Neurofunctional correlates of emotions and reward in game-based learning

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ABSTRACT

Accumulating evidence identifies emotions as drivers of effective learning. In parallel, game-based learning was found to emotionally engage learners, allegedly harnessing the fundamental tie between emotions and cognition. Questioning further whether and how game-based learning elicit emotional processes, the current fMRI study examined the neurofunctional correlates of game-based learning by directly comparing a game-based and a non-game-based version of a digital learning task. We evaluated neurofunctional activation patterns within a comprehensive set of brain areas involved in emotional and reward processes (e.g. amygdala or ventral tegmental area) when participants received feedback. With only a few exceptions, decoding of these brain areas' activation patterns indicated predominantly stronger relative activation in the game-based task version. As such, our results substantiate on a neurofunctional level that game-based learning leads to an invigoration of learning processes through processes of reward and emotional engagement.

1. Introduction

Playing digital games is highly popular and a widespread phenomenon in today's society (Lenhart et al., 2008). Moreover, engaging in playful activities is deeply rooted in human nature (Huizinga et al., 2006; Gray, 2013; Panksepp, 2005). In fact, it was suggested that play, just as anger, fear, lust, and grief is among the emotional systems of the brain that already exist in newborns (Panksepp, 2005). Playing is a necessary prerequisite to acquire cultural skills (Huizinga et al., 2006), the acknowledged way for children to learn (Edwards, 2002) and generally serves essential evolutionary purposes (Ryan & Deci, 2000). Contemporarily, we understand play as an intrinsically purposeful activity (Wilkinson, 2016) which is also voluntarily used to, for instance, surpass obstacles (Krouse et al., 2011; Suits, 2005).

Next to reaching goals such as winning a competition or gaining skills, enjoyment and emotional experiences are often the incentive to play digital and non-digital games, making emotions indissociable from games (Yannakakis & Paiva, 2015). Not only do emotions play a crucial role in our everyday lives (Dixon et al., 2017), they most likely are the trigger for positive experiences with games (Yannakakis & Paiva, 2015). It only makes sense that they are recognized as an essential element in game design (Baharom, Tan, & Idris, 2014; Karpouzis & Yannakakis, 2016) and their evoking and handling is an integral part of a positive gaming experience.

Educational games try to recruit similar mechanisms for more dedicated purposes. They facilitate learning processes by, for instance, keeping up motivation, effort, and – in best case scenarios – flow as well as engagement during playing. Research in this context frequently

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highlights the impact of positive affect in game-based learning, such as engaged concentration, joy, and excitement for learning (Sabourin & Lester, 2014). Positive affect is argued to positively impact learning, motivation, and information processing in traditional (Pekrun & Linnenbrink-Garcia, 2014) but also digital learning settings (Um et al., 2012). However, game elements might facilitate not only positive but also negative emotions (Ninaus et al., 2019). Importantly, though, negative emotions such as frustration, which can occur when learners make errors (Kapoor et al., 2007), have also been linked to more positive learning outcomes (Shute et al., 2015). The authors argued that a learner needs to be sufficiently invested in the actual learning process to actually perceive frustration, which is in line with research suggesting overall increased emotional engagement (positive and negative emotions) in game-based learning (Ninaus et al., 2019). Moreover, in the context of games, even negative affective states such as frustration can be part of an enjoyable and challenging overall gaming experience (Gee, 2007).

From a neurocognitive perspective, emotions and cognition were historically conceptualized as separate systems (Y. Liu et al., 2009). Now they are understood as the result of dynamic interactions (Pessoa, 2008). Accumulating evidence states that emotions substantially influence human cognition, including perception, attention, learning, memory, reasoning, and problem-solving (Barbas, 2000; Brosch et al., 2013; Y. Liu et al., 2009; Pessoa, 2008; Tyng et al., 2017). For instance, inducing positive but also negative emotions when learning can improve memory consolidation (Nielson & Powless, 2007), emotional targets are detected more rapidly among distractors than neutral targets (Ohman et al., 2001), and emotional arousal was observed to facilitate consolidation of long-term memories (Hamann, 2001; Phelps, 2004). This means that by emotionally engaging the player, cognitive processes can be impacted to facilitate learning processes (Greipl et al., 2020; Plass et al., 2015). Successful learning games may therefore account for and accommodate emotional, but also other faculties like cognitive resources that are in constant interaction (Greipl et al., 2020). However, such higher emotional engagement suggested for game-based learning was not yet substantiated on a neurofunctional level.

For the current study we adapted a well evaluated educational game (Kiili et al., 2018; Ninaus et al., 2017, 2019) such that it can be played within a functional magnetic resonance imaging (fMRI) scanner and compared it directly to a content-wise identical non-game-based version. This allowed for an in-depth evaluation of the involvement of reward and emotional processes in a game-based learning scenario.

A recent review of neural correlates addressing video game play in general highlights various, predominantly cognitive aspects. The authors report ample evidence on the involvement of reward processing related to gaming but only indirect links to emotional processing, for instance, within the context of flow experiences or addiction (Palaus et al., 2017). A general synthesis of the neural underpinnings of gaming remains difficult because neuroscientific evidence related to game-based learning is rare. To our knowledge, only two studies investigated this specifically.

First, using fMRI Howard-Jones et al. (2016) reported reduced activation of default-mode network hubs but increased activation of the ventral striatum (VS) when learning sessions comprised game elements. Second, a study by Cole et al. (2012) compared brain activation during actively playing the serious game *Re-Mission* (designed for young cancer patients) to passively watching another participant play. This contrast revealed increased activation in the anterior cingulate cortex (aCC), anterior insula (aINS), putamen (PUT), and thalamus (THA) for active playing. Contrasting active playing to a rest condition revealed a widespread network of activation including thalamus (THA), anterior insula (aINS), and putamen (PUT).

Most of the areas found active for game-based learning in both studies are well in line with expectations derived from the neuroscientific literature regarding reward-related activation, including positive (i.e. reward/win) and negative (i.e. punishment/loss) valences of reward processing (Silverman et al., 2015; Sescousse et al., 2013). Moreover, with the anterior insula (aINS) and the nucleus accumbens (NAC), areas typically found active for experiences of emotions and/or pleasure (Kurth et al., 2010; Berridge & Kringelbach, 2015) seemed to be involved as well. Taken together, it seems that increased activation of the so-called reward system may be central for educational benefits of game-based learning (Howard-Jones et al., 2016).

Remarkably, the relationship between reward and emotions seems to be very close (Rolls, 2005). However, what is still missing is a systematic investigation on whether feedback about a players' performance within a game-based learning environment reflects this concordant rewarding (and therefore emotional) nature. As this does not necessarily result in observable behavior, it is essential to evaluate activation in brain areas specifically associated with processing emotions and rewards. Accordingly, the two central aspects of our study were: a) In addition to well-known reward mechanisms, we particularly focus on correlates of emotions and emotional processing as an immediate result of the interaction with a game-based learning environment. b) We do so by comparing a game-based (involving game elements such as a narrative and visual aesthetics, etc.) and a stripped non-game-based version of the same digital math learning task. We particularly focused on the phase of the respective task version in which players received feedback (henceforth referred to as feedback episodes). Feedback embedded in the game-based version might be perceived more emotionally engaging and rewarding (for a more comprehensive view on personal/contextual factors influencing how positive/negative feedback is interpreted see e.g. Fishbach et al., 2010) as compared to its non-game-based equivalent and should, therefore, yield differential activation in specific brain regions involved in processing emotions and rewards which we considered regions of interest for our study.

On a subcortical level, we selected areas known for their involvement in various kinds of emotional processing and/or pleasure experiences, such as the amygdala (AMY) (Sergerie et al., 2008), ventral pallidum (VeP) (Johnston & Olson, 2015) as well as striatal areas including the nucleus accumbens (NAC) (Berridge & Kringelbach, 2015), the putamen (PUT), and the caudate nucleus (CAU) (Waraczynski, 2006; Silverman et al., 2015). Moreover, we considered starting points of the dopaminergic pathway such as the ventral tegmental areas as well as substantia nigra (pars reticulata, SNr) (Garris et al., 1993; Nieuwenhuys, 1985), crucially involved in reward processes (Knutson et al., 2000). Importantly, we need to note that some of those regions are also involved in processing negative emotions. More specifically, positive and negative emotions seem to be processed in several valence-insensitive brain regions making a differentiation between positive and negative emotions on levels of brain activity very difficult (Lindquist et al., 2016).

Cortically, the anterior insula (aINS) and the frontal medial cortex (fmC) seem to be among the areas strongly linked to emotional processing (Phan et al., 2002; O'Doherty et al., 2001; Kurth et al., 2010; see also Lindquist et al., 2016) whereas activation of the medial orbital cortex (foC) was identified as a neural correlate of pleasure (Berridge & Kringelbach, 2013). Additionally, anterior and posterior parts of the cingulate cortex (aCC and pCC) were frequently found to be involved in reward processing (Silverman et al., 2015).

2. Methods

2.1. Participants

47 right-handed adult participants took part in the study. We excluded five participants from data analysis. One participant due to problems with vision correction and four subjects due to technical problems. Thus, data from 42 participants (age: M = 24.4, SD = 3.16, female = 23, male = 19), entered the analyses. All participants were German native speakers with normal or corrected to normal vision and reported no history of psychiatric or neurological disorders or drug abuse. The study was approved by the local Ethics Committee of the Medical Faculty of the University of Tübingen. Participants provided

written informed consent prior to the study and received monetary compensation for their participation. All investigations were carried out in accordance with the relevant guidelines and regulations.

2.2. Study design

The study employed a 2 × 2 design discerning the factors presentation format (game-based vs. non-game-based) and content (fractions vs. letter pairs) with the letter pair condition serving as a control condition (see Fig. 1). Analyses of data focused on feedback episodes (see Fig. 2). The study comprised two consecutive scanning sessions for each participant, randomly starting with either the game-based (i.e., fractions and letter pairs) or the non-game-based (i.e., fractions and letter pairs) task version/presentation format. That is, during each scanning session, both items from the fraction as well as the letter pair condition were presented. However, the control (i.e. letter pairs) items were not considered for the current analysis, as these will be primarily used for investigating aspects of numerical cognition. Further, we implemented an additional baseline level represented by the resting condition.

The core of our game-based learning scenario is a number line estimation task (Siegler & Booth, 2004). In this task, participants had to indicate the spatial position of a target fraction on a number line with only its endpoints specified (e.g. “Where goes 11/23 on a number line ranging from 0 to 1?“, see also Fig. 2). Hence, our game trains understanding of fraction magnitude. Dependent on the accuracy with which the fraction is indicated on the number line, the player succeeded or failed in solving the task and received positive or negative feedback, respectively (see Fig. 2). The threshold for an answer to be correct is a maximum deviation of ±10% from the target position (see below for a more detailed description). In the current experiment, we used two different versions of the fraction number line estimation task. The game-based version was a derivate of the fraction learning game NumberTrace (based on Semideus with reproduced graphics and storyline; see e.g. Kiili et al., 2018 and https://webpages.tuni.fi/gamelab/), however, adapted to the requirements of an fMRI experiment. In particular, we discarded most graphical and visual extras as well as additional elements not tied to the execution of the task (e.g. the possibility to activate supportive features that help to solve the task, such as segmentation of the number line). At the same time, we kept necessary game elements, including the avatar that is walking on the number line and the game's visual appearance. The latter comprises a minimum of textures such as a static background and movement-related animations (e.g. walking, indicating the position on the number line, and feedback animations). This way, the game-based version was still embedded in a narrative with appealing visual aesthetics (see Fig. 1).

After indicating the estimated position of a given target fraction on the number line, positive or negative feedback (happy or sad dog; see Fig. 2) was given according to the performance (accuracy) of participants to increase emotional engagement. Additionally, the game-based version provided gradual feedback. Depending on the accuracy of the correct response, the dog shows a cheering reaction of different intensity from relatively neutral (≥90% accuracy, i.e., neutral facial expression, weak tail wagging) to very happy (=100%, i.e., gladdened facial expression with tongue hanging out and pronounced tail wagging).

The non-game-based version was reduced to only the basic mechanisms necessary to perform the number line estimation task and maintain comparability to the game-based version (see Fig. 1). All graphic elements, textures as well as animations were removed and, for instance, replaced by simple geometric figures and mostly scaled to black/grey/white. The result was a conventional number line estimation task that comprised none of the game-based aspects. Yet, participants received positive/negative feedback according to their performance in the task in the form of a green tick or a red cross (positive and negative feedback, respectively; see Fig. 2).

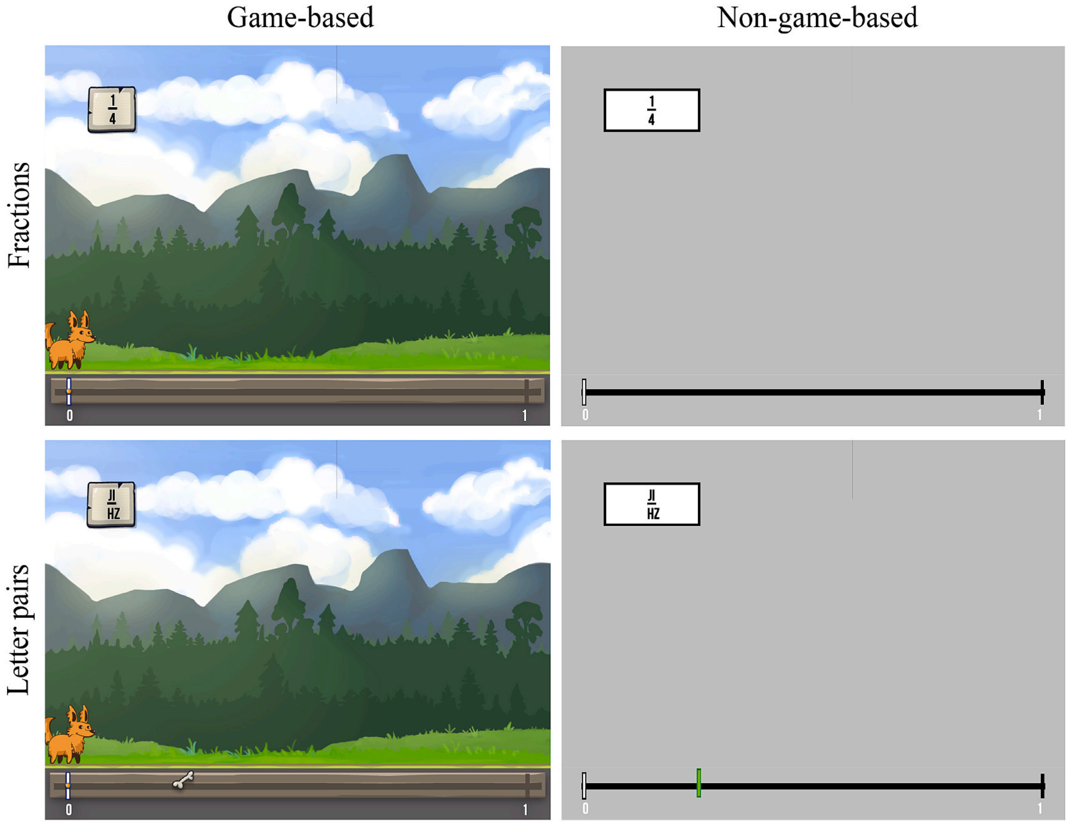


Fig. 1. Illustration of presentation format and content. Top left: game-based | fraction, top right: non-game-based | fraction, bottom left: game-based | letter pair; bottom-right: non-game-based | letter pair.

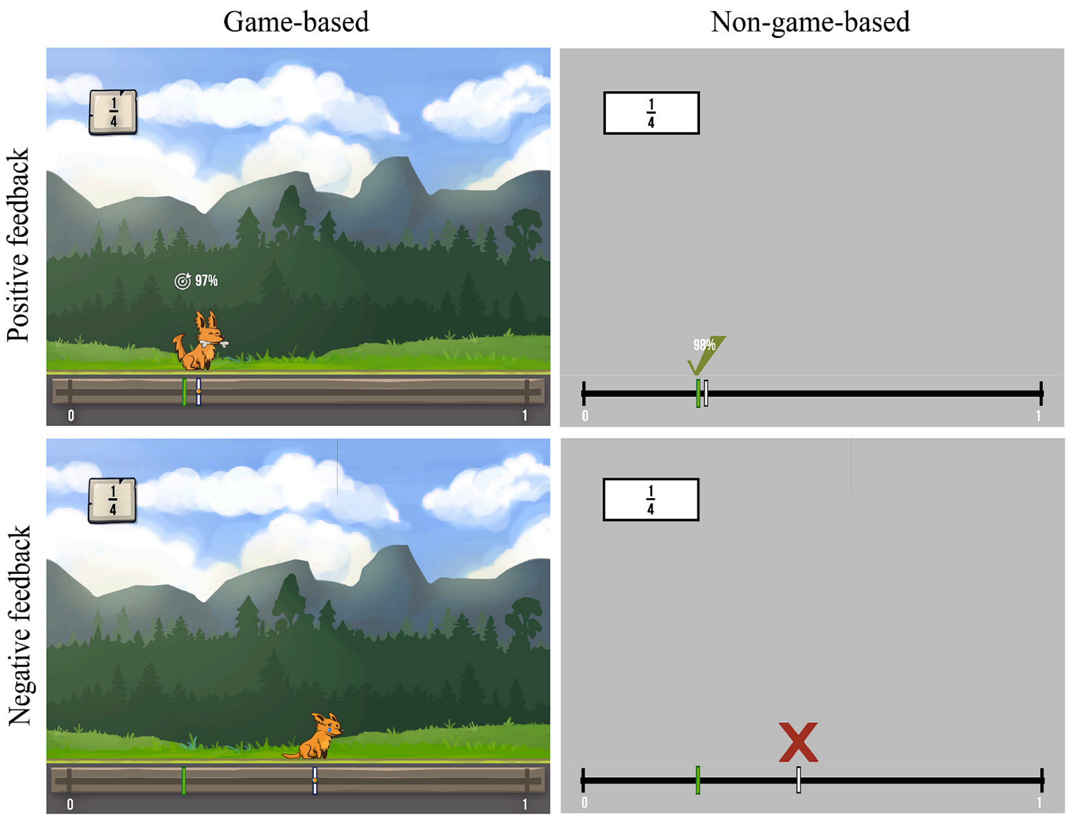


Fig. 2. Illustration of feedback in the fraction condition. Top (positive feedback) left: game-based | positive feedback (dog displaying a happy face), top right: non-game-based | positive feedback (green tick), bottom (negative feedback) left: game-based | negative feedback (dog displaying a sad face); bottom-right: non-game-based | negative feedback (red cross).

In both versions, inputs such as moving the avatar/slider (i.e. left/right button for movements to the left/right) or confirm the position on the number line (i.e. middle button) were given one-handed on an MRI-compatible button box. A response was considered correct when the location of the respective fraction was estimated within ±10% deviation from the correct position on the number line. Participants could only give one answer per item and in case no answer was provided, the button for solving the task was triggered automatically after 12 s to ensure progress of the task.

In addition to the fraction (estimation) condition where actual fractions needed to be estimated, we introduced a control condition for both task versions/presentation formats, in which a position on the number line had still to be indicated, but the correct positions were shown on the screen and numerator/denominator of the fraction were replaced by letters (two-digit pairs were matched to letter pairs). This means that in the control condition no fraction/magnitude estimation had to be performed whereas the mechanics of the game remained unaffected. Specifically, the solutions given for the items in the control condition matched the correct positions of the items from the game/non-game-based task of the corresponding session. However, the control condition (i.e. game-based and non-game-based letter pair trials) was not part of the current analyses as it was intended to analyse the neural correlates of fraction processing rather than the differentiation between game- and non-game-based learning.

2.3. Items and stimulus set

The item sets comprised fractions with a numerator as well as denominator ranging from 2 to 29. From all possible fractions, two balanced (equally distributed between 0 and 1) sets of fractions containing 48 fraction items each were created. Both presentation formats (i.e. variants of the task – game-based and non-game-based) used each item sets in a counterbalanced way across participants to avoid that found effects can be attributed to the selected itemset. The same fractions of the two item sets were used to create another 2 sets of control items, in which fractions were replaced by letter pairs. Furthermore, matching sets of fraction and letter pair items were used within a session. During scanning, the game engine randomly drew a block of either 4 fraction or letter pair items from the respective pool. This way, both item order as well as the sequence of conditions within each session have been randomized. Each block of 4 items (either fractions or letter pairs) was followed by a 23s resting period in this fixed order. After each resting period, the game engine again randomly chose 4 new items from either the fraction or the letter pair condition until all items were presented once, resulting in 12 blocks of 4 fraction items and 12 blocks of 4 letter pair items (see Fig. 3). This results in 48 fraction items and 48 letter pair (control) items per session (96 in total) and one participant being presented with 192 items in total across the two scanning sessions (game-based and non-game-based). Again, the current work focussed on fraction items exclusively.

With respect to the procedure, one session contained 12 blocks of 4 fraction items and 12 blocks of 4 letter pair items each. A baseline (rest) condition was accomplished by including pauses between the blocks. Therefore, 24 blocks intermediated by 23 s resting periods totaled in 9 min and 12 s resting time per session. Thus, there was 18 min and 24 s of rest for each participant throughout the experiment.

The average duration of a trial (duration of one trial refers to the time interval between the onset of one item until the start of the next item) was 6.96 s. One scanning session lasted approximately 21 min (excluding i.e. structural brain scans) depending on the task performance of the participants.

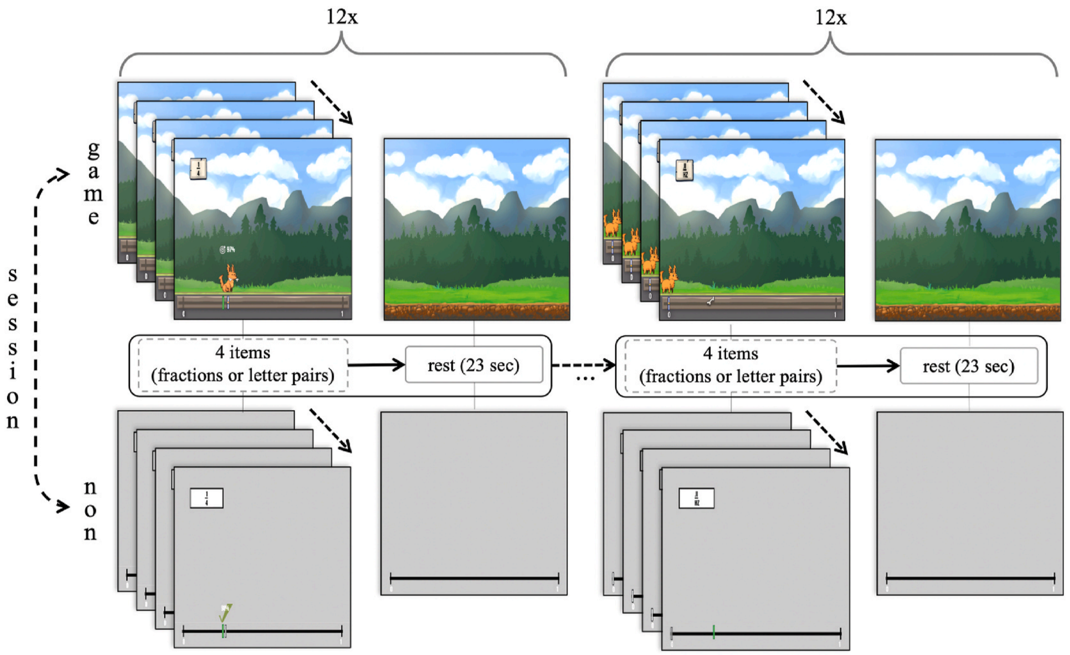


Fig. 3. Illustration of the scanning procedure and timings. Every subject played both the game-based (game) and non-game-based (non) version in separate sessions. Sessions were intermediated by a structural scan. Solid arrows indicate fixed orders, whereas dotted arrows indicate randomization across sample/items.

2.4. *Measures*

After each scanning session, participants had to fill in the User Experience Questionnaire (UEQ) (Laugwitz et al., 2006) to assess basic experiential qualities of both task versions on six subscales. With bipolar ratings from 1 to 7, the UEQ evaluates pragmatic usability aspects with three subscales [i.e., efficiency (4 items), e.g. “quick vs. slow”; perspicuity (4 items), e.g. “complicated – simple”; dependability (3 items), e.g. “predictable – unpredictable”], hedonic aspects of user experience with 2 subscales [i.e., novelty (3 items), e.g. “creative – unimaginative”; stimulation (3 items), e.g. “boring – thrilling”], and attractiveness with one subscale (6 items; e.g. “pleasant – unpleasant”).

2.5. *MRI and fMRI data acquisition*

A high-resolution T1-weighted anatomical scan was acquired using a 3T Siemens Magnetom Prisma MRI system (Siemens AG; Erlangen, Germany) equipped with a 64-channel head-neck matrix coil (TR = 2400 s, matrix = 256 × 256, 176 slices, voxel size = 1.0 × 1.0 × 1.0 mm^3; FOV = 256 mm, TE = 2.92 ms; flip angle = 8°). The anatomical scan was always performed at the end of each session.

Functional T2*-weighted images were obtained using a multiband gradient-echo echo planar imaging sequence (EPI; TR = 792 ms; TE = 30 ms; flip angle = 58°; FOV = 192 mm, 64 × 64 matrix; 48 slices, voxel size = 3.0 × 3.0 × 3.0 mm^3). Total scanning time was approximately 55–65 min.

2.6. *Analyses*

2.6.1. *Behavioural analysis*

We evaluated basic performance measures (i.e., error rate and reaction times) for the two task versions (i.e., game-based vs. non-game-based). In particular, we compared the percentage of error (relative frequency of correctly solved items; ≥90% accuracy), item completion time (stimulus onset till button press) and estimation accuracy of all items for each participant. We used paired sample *t*-tests for comparisons across task versions. In addition, we evaluated differences between conditions along the six subscales of the UEQ (efficiency, perspicuity, dependability, novelty, stimulation, attractiveness). FDR correction (Benjamini & Hochberg, 1995) was applied to correct for multiple testing.

2.6.2. *Imaging analysis*

Our analyses approach comprised three levels involving univariate and multivariate procedures. In the univariate analyses we compared the average activation level in a voxel/brain region between the game-based and non-game-based condition for fraction items. Our multivariate approach then looked for differences in distributed patterns of activity over multiple voxels related to these varying task conditions (Popov et al., 2018), usually referred to as multi-voxel pattern analysis (MVPA). Both scenarios used the presentation format/task version (game-based vs. non-game-based) as independent variable. In the univariate analysis, the average BOLD signal of single voxels or a set of voxel was the dependent variable used to estimate beta regressors, which were subsequently used as the dependent variables in the multivariate analysis.

First, we used Statistical Parametric Mapping software (SPM12, Wellcome Center for Human Neuroimaging; http://www.fil.ion.ucl.ac.uk/spm) for preprocessing and intrasubject modelling (first-level analysis). Second, we performed percent-signal extraction using MarsBar (http://marsbar.sourceforge.net) for the ROIs described below. Here, BOLD signal change parameters were obtained separately for each ROI and participant. These parameters were subsequently compared on a group level using t-tests. For instance, participants’ signal change parameters for the amygdala were compared between the game-based and non-game-based condition. Third, we used intra-subject single-trial based pattern recognition in the same ROIs to complement the univariate analyses with more sensitive multivariate models to further validate our results. A single trial refers to (the reception of feedback by) completing one fraction item. Whenever required, correction for multiple comparison using the FDR-method (Benjamini & Hochberg, 1995) was applied. These analysis steps are described in more detail below.

2.6.2.1. Preprocessing. First, we applied artifact correction using ArtRepair (Mazaika et al., 2007), identifying bad slices and eliminating false activations outside the head. Bad slices were repaired using a liberal outlier threshold value of 18 and linear interpolation of the before and after volumes. Out of 84 data sets (one dataset represents a scanning session from one participant, therefore 42 participants x 2 sessions), 82 had at least one bad slice repaired. On average, around 5% of the slices were repaired per participant. Next, we used the FieldMap toolbox to calculate field maps of magnetic field inhomogeneities. These field maps were then used to unwarp fMRI data according to field distortions. Subsequently, EPI images were realigned and transformed into the Montreal Neurological Institute (MNI) standard space. No slice time correction was performed. The resulting functional mean image was used to co-register previously segmented structural images. Structural and functional images were interpolated using 4th-degree B-Spline with 3 mm (EPI) and 1 mm (T1) voxel sizes. Smoothing was performed using a 5 mm full width at half maximum (FWHM) of the Gaussian smoothing kernel. Data were high-pass filtered (128 s) to remove low-frequency noise components and corrected for autocorrelation assuming an AR (1) process. Brain activity was convolved over all trials with the canonical hemodynamic response function (HRF) and its first time derivative.

2.6.2.2. First level analysis. After preprocessing, a general linear model (GLM) over all trials was defined using the canonical HRF and its first time derivative. Inclusion of all trials has several advantages: First, the number of trials is completely balanced and constant across participants. This is especially useful for later MVPA-analysis, where balancing training and test data is highly recommended (e.g. Weiss & Provost, 2001). Another reason is that by far most trials were solved successfully (>90%). Thus, negative feedback only accounts for a small portion of trials overall. The negative to positive trial ratio was approximately equal for both sessions (see behavioural results).

Feedback episodes of all game-based items, all non-game-based items, rest sequences, the onset of a new item, and button presses (left/right direction) were modeled separately. Thus, the GLM had 5 regressors in total [feedback episodes (reception of feedback) in the game-based condition, feedback episodes (reception of feedback) in the non-game-based condition, rest, item onset, left/right button presses] along with 6 movement parameters from preprocessing to capture signal variations due to head motion for each of the two sessions. Critically, feedback episodes lasted exactly 2 s across conditions.

2.6.2.3. First-level modeling. ROI analyses: We defined a set of brain areas as regions of interest (ROIs) that were previously reported to be critically involved in either emotion or reward processing. In addition, we examined strongly interconnected areas, sometimes called hubs, that specifically integrate cognitive and emotional information, which could further be interesting with respect to the formation of memory representations. Following the suggestion by Poldrack (2007) we used meta-analytic results for ROI definition and extraction where applicable. This was the case for the amygdala (AMY), for which we used the connectivity-based parcellation (CBP) of the whole bilateral amygdala from Bzdok and colleagues' (2013) meta-analysis, and for the anterior insula (aINS), for which we extracted the corresponding regional information from Kurth et al. (2010). In all other cases, we extracted ROI masks from probabilistic atlases. In particular, we extracted the ROI masks for hippocampus (HIP), anterior cingulate cortex (aCC), posterior cingulate cortex (pCC), frontal medial cortex (fmC), and frontal orbital cortex (foC) from the *Harvard-Oxford* cortical and subcortical structural *atlas* as distributed with FSL (FMRIB Software Library, 2016, Atlases Overview; available at: http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/Atlases). Positional information for caudate nucleus (CAU), nucleus accumbens (NAC), putamen (PUT), substantia nigra pars reticulata (SNr) and ventral tegmental area (VTA) was extracted from the probabilistic high resolution atlas of human subcortical brain nuclei by Pauli et al. (2018).

Mean percent signal change (PSC) relative to baseline within each ROI for each game-based and non-game-based fraction trial/item (i.e. feedback episodes to letter pair items were omitted from the analysis) was extracted using the MarsBar toolbox (http://marsbar.sourceforge.net).

MVPA analysis: Unsmoothed images were used for multivariate analysis to preserve maximal spatial information. We extracted beta-images for every trial of relevant regressors (e.g. feedback episodes) for the ROIs to perform pattern analysis based on single trials within single subjects. Based on the same first-level model as before, we followed a multi-regressor approach, similar to what was described by Rissman et al. (2004), that estimates a single model with all trials represented by individual regressors. The resulting beta-images were used to perform a binary classification with cross-validation using *The Decoding Toolbox* (Hebart et al., 2015). Classification was performed using the popular support vector machine algorithm (SVM) that separates data points into two classes using a hyperplane with the largest amount of margin. As all 96 fraction trials (48 per condition game-based vs. non-game-based) were included, classification was validated by a leave-one-block-per-class-out cross validation procedure with 12 folds. That means that every fold was trained on a balanced set of 88 items (44 per condition) and tested on 8 items, a block of 4 items per condition. Subsequently, permutation tests based on 1000 permutations were performed to obtain statistical estimates (p-/z-values) about the achieved classification accuracy. This procedure was repeated for each subject and each ROI.

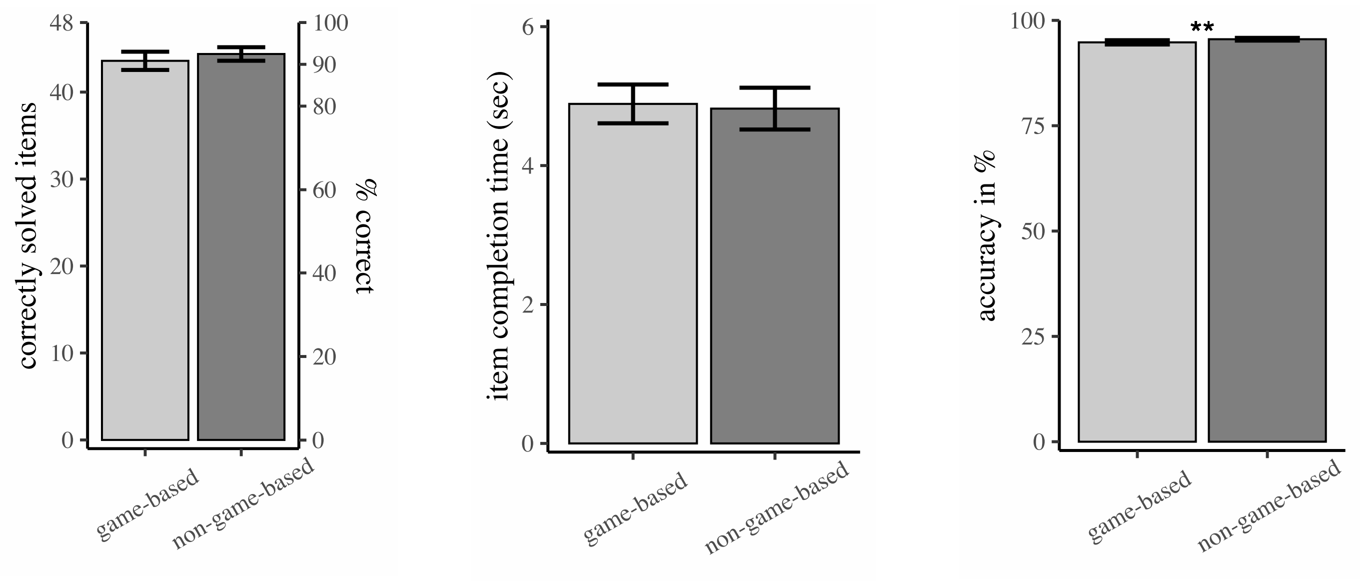
Gained z-values from testing for individual significance of classification accuracy were used to generate summary statistics. One-sided *t*-tests for each ROI were applied to evaluate whether the sample mean of z-scores significantly exceeds a threshold of $z = 1.65$. Thus, $z = 1.65$ is the significance threshold for a one-tailed test at an alpha level of $p < .05$).

3. Results

3.1. Behavioural results

Analysis of performance differences indicated no significant differences between the game-based and the non-game-based version of the task regarding the number of correctly positioned fractions (game-based: $M = 43.6$, $SD = 3.36$; non-game-based: $M = 44.38$, $SD = 2.5$; $t(41) = 1.85$, $MD = -0.79$, CI [-1.64, 0.07], $p = .07$, $d = 0.29$). Moreover, there was no significant difference in terms of how much time participants needed to solve the items (game-based: $M = 5.41$, $SD = 1.14$; non-game-based: $M = 5.40$, $SD = 1.10$, $t(41) = 0.11$, $MD = 0.01$, CI [-0.20, 0.22], $p = .91$, $d = 0.02$). However, there was a significant difference for the accuracy of the number line estimations ($t(41) = -2.99$, $MD = -0.54$, CI [-0.91, −0.18], $p < .01$, $d = 0.46$). Fractions were estimated more accurately in the non-game-based version ($M = 96.50$, $SD = 0.46$) as compared to the game-based version of the task ($M = 95.95$, $SD = 1.06$; see Fig. 4 for illustrations of performance differences).

Significant differences for subjective ratings (see Fig. 5) were observed for four out of six subscales. The game-based version was rated more attractive (game-based: $M = 1.89$, $SD = 0.79$, *Cronbach's* $\alpha = 0.71$; non-game-based: $M = -0.04$, $SD = 1.02$, Cronbach's $\alpha = 0.54$; $t(41) = 9.84$, $MD = 1.93$, CI [1.54, 2.33], $p < .001$, $d = 1.52$), more novel (game-based: $M = 1.55$, $SD = 0.68$, *Cronbach's* $\alpha = 0.79$; non-game-based: $M = -1.55$, $SD = 0.95$, Cronbach's $\alpha = 0.79$; $t(41) = 16.01$, $MD = 3.10$, CI [2.71, 3.49], $p < .001$, $d = 2.47$), and stimulating (game-based: $M = 1.21$, $SD = 0.90$, *Cronbach's* $\alpha = 0.75$; non-game-based: $M = -0.51$, $SD = 0.90$, Cronbach's $\alpha = 0.59$; $t(41) = 9.78$, $MD = 1.72$, CI [1.37, 2.08], $p < .001$, $d = 1.51$). However, on a more pragmatic level, the non-game-based version was rated to be more efficient (game-based: $M = 0.95$, $SD = 0.71$, *Cronbach's* $\alpha = 0.80$; non-game-based: $M = 1.54$, $SD = 0.70$, Cronbach's $\alpha = 0.68$; $t(41) = -4.08$, $MD = -0.59$, CI [-0.89, −0.30], $p < .001$, $d = 0.63$; see Fig. 5). No significant differences were found for perspicuity (game-based: $M = 2.19$, $SD = 0.67$, *Cronbach's* $\alpha = 0.79$; non-game-based: $M = 2.30$, $SD = 0.65$, Cronbach's $\alpha = 0.65$; $t(41) =$



(a) (b) (c)

Fig. 4. (a): The number of (maximal 48) fractions that were solved with ≥90% accuracy (left axis: absolute averaged number of items, right axis: average percentage of correctly solved items). (b): The average time in seconds subjects needed to estimate one fraction along the number line. (c): The average accuracy of estimations from all fractions presented during playing.

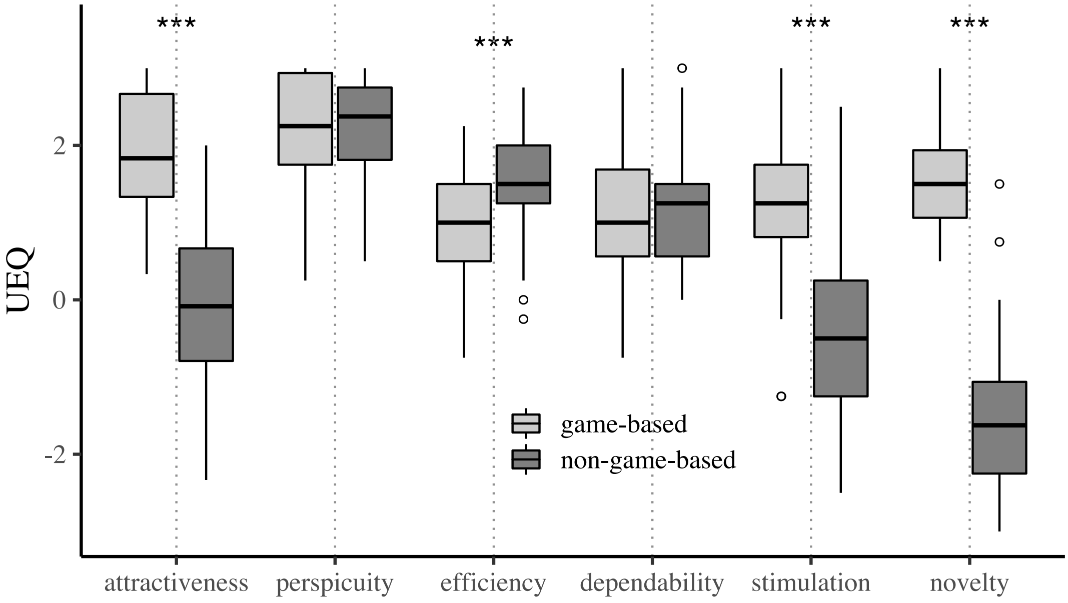


Fig. 5. Mean ratings from the user experience questionnaire (UEQ).

-1.04, *MD* = −0.11, CI [-0.35, 0.11], *p* = .303, *d* = 0.16) and dependability (game-based: *M* = 1.09, *SD* = 0.81, *Cronbach's α* = 0.77; non-game-based: *M* = 1.21, *SD* = 0.81, Cronbach's *α* = 0.66; *t*(41) = -0.96, *MD* = −0.12, CI [-0.39, 0.14], *p* = .343, *d* = 0.15).

3.2. Imaging results

3.2.1. Univariate analysis

Subcortical areas that showed a significant difference in BOLD signal change, as well as increased relative activation during feedback episodes in the game-based as compared to the non-game-based version of the task, were amygdala (AMY), putamen (PUT), substantia nigra (pars reticulata, SNr) and ventral tegmental area (VTA). Cortical areas with significant activation differences in the same direction were anterior Insula (aINS) and posterior cingulate cortex (pCC). The only area that showed a statistically not significant tendency in the opposite direction (i.e., higher activation for the non-game-based than the game-based task) was the frontal medial cortex (fmC) (please refer to Table 1 for statistical details on the results described in this paragraph; see also Fig. 6 upper panel).

3.2.2. Multivariate pattern analysis

Results from multivariate analysis (see Fig. 6 lower panel) were largely consistent with those of the univariate analysis. Subcortical areas for which there was a significant difference between activation patterns for feedback episodes of the game-based and non-game-based version of the task were the amygdala (AMY), hippocampus (HIP), caudate nucleus (CAU), putamen (PUT) and substantia nigra (pars reticulata, SNr).

Table 1
Complete table of group statistics results of all ROIs in activation estimates and decoding results. Mean difference refers to the absolute difference in group means. Chance level (50%) was subtracted from mean accuracy values. Please note, results did not change substantially when only trials with positive feedback were considered for the analyses of neurofunctional data..

2nd-level statistics (N = 42)	Percent signal change, paired t-tests			MVPA, z-scores (p-values) evaluated by single subject permutation tests, subsequent t-tests (z-scores against 1.65, one-sided test)			
ROI	*p*-value (FDR-corrected)	*p*-value (uncorrected)	mean difference	mean(acc)	mean (z)	sd(z)	p-value (H0 = z ≤ 1.65)
Amygdala (AMY)	.032	.014	0.035	14.112	2.359	0.694	<.001
Anterior Insula (aINS)	<.001	<.001	0.053	15.724	2.440	0.702	<.001
Hippocampus (HIP)	.092	.072	0.018	17.411	2.648	0.564	<.001
Anterior Cingulate Cortex (aCC)	.068	.041	0.022	18.824	2.856	0.388	<.001
Posterior Cingulate Cortex (pCC)	.032	.016	0.028	16.667	2.615	0.691	<.001
Frontal medial Cortex (fmC)	.068	.044	−0.027	16.840	2.571	0.641	<.001
Frontal orbital Cortex (foC)	.075	.054	0.022	18.452	2.753	0.534	<.001
Caudate Nucleus (CAU)	.196	.196	0.014	15.749	2.499	0.608	<.001
Nucleus Accumbens (NAC)	.159	.148	0.035	10.640	1.803	0.923	.145
Putamen (PUT)	.002	<.001	0.043	15.551	2.608	0.507	<.001
Substantia Nigra, pars reticulata (SNr)	.006	.002	0.051	11.682	1.964	0.814	.008
Ventral Pallidum (VeP)	.126	.108	0.030	6.920	1.351	0.827	.988
Ventral tegmental area (VTA)	.001	<.001	0.048	9.251	1.662	0.864	.465

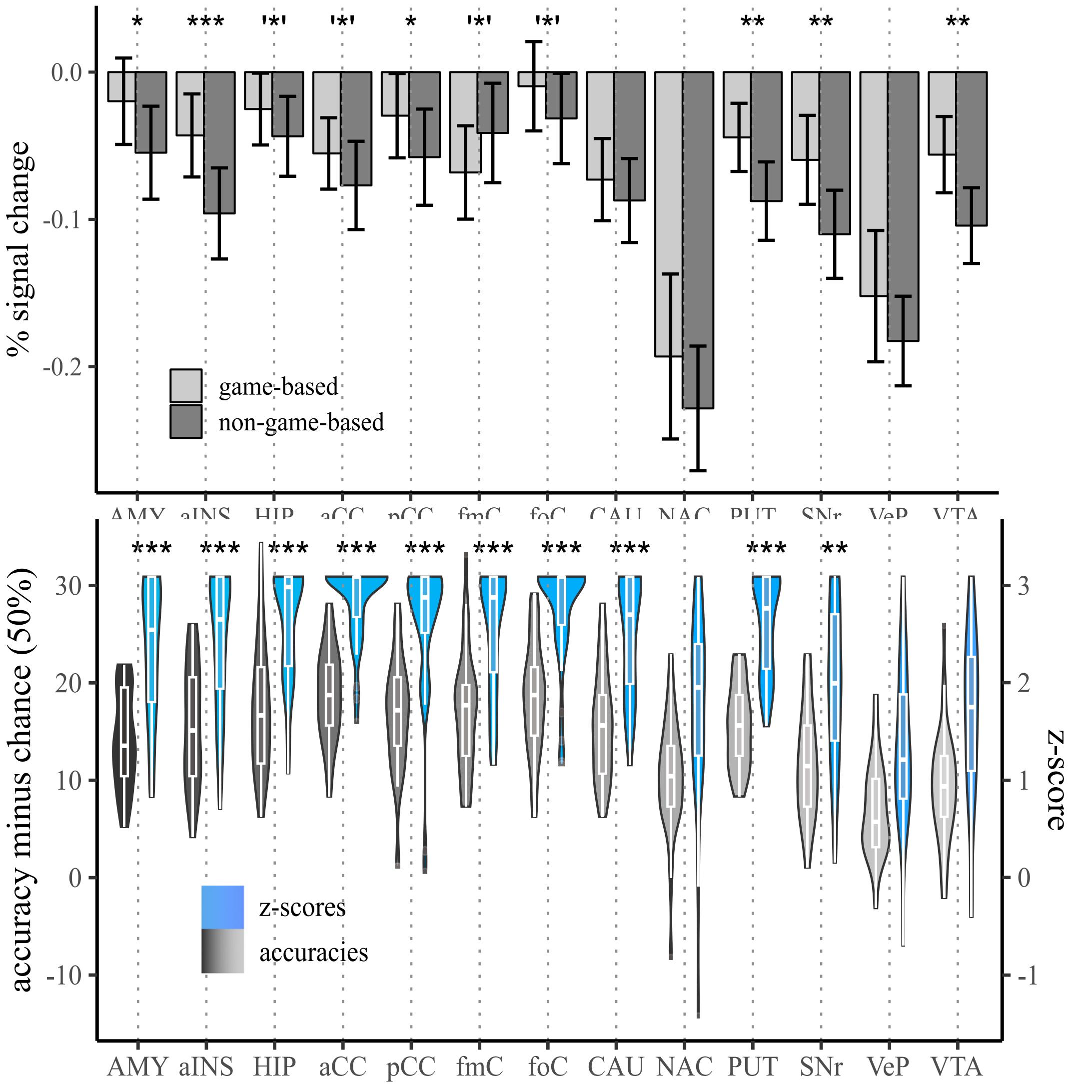


Fig. 6. Top: Univariate Analysis. Bottom: Multivoxel Pattern Analysis. Value “0” on the y-axis represents classification at chance level (50% chance level for binary classification were subtracted from percentage values). ROI abbreviations: AMY - Amygdala; aINS - anterior Insula; HIP – Hippo-campus; aCC - anterior Cingulate Cortex; pCC - posterior Cingulate Cortex; fmC - frontal medial Cortex; foC – frontal orbital Cortex; CAU – Caudate nucleus; NAC – nucleus accumbens; PUT – Putamen; SNr – substantia nigra pars reticulata; VeP – ventral pallidum; VTA – ventral tegmental area.

Cortical areas for which we observed significant differences in activation patterns were the anterior insula (aINS), anterior cingulate cortex (aCC), posterior cingulate cortex (pCC), frontal medial cortex (fmC) and frontal orbital cortex (foC, please refer to Table 1 for statistical details). It is worth noting that the frontal medial cortex (fmC) was the only region that revealed a statistically not significant trend in the opposite direction, meaning it showed descriptively higher activation for the non-game-based as compared to the game-based version of the task.

Due to the more complex multivariate model and the higher sensitivity of this analysis approach, additional regions compared to the univariate analysis were identified for which there were significant differences in activation patterns such as the hippocampus (HIP), anterior cingulate cortex (aCC), frontal medial/orbital cortex (fmC, foC) and caudate nucleus (CAU).

Only for the ventral tegmental area (VTA), the reverse was true: univariate analysis indicated a significant difference in mean activation, but multivariate analysis did not substantiate this pattern. However, there are at least two reasons why this finding should be treated with caution. First, the ventral tegmental area (VTA) is a comparably small area, thus, the classifier had to rely on less features to find a pattern. Second, our statistical threshold is quite conservative because mean decoding accuracy of the ventral tegmental area (VTA) is still over 59% (which is equivalent to a mean z-score of 1.66). This means that there may still be a non-neglectable proportion of participants for whom a meaningful pattern was found in this respective brain area (please refer to Table 1 for the statistical details).

4. Discussion

In the present study, we aimed at investigating the neural correlates of emotional engagement through game elements added to a numerical learning task. Overall, the results of this study suggest that, measured by the feedback episode of the game, interacting with the game-based version of the task indeed led to increased neural response in brain areas associated with emotion and reward processing. While these brain areas may all contribute to a closely integrated network, neurofunctional responses to the game-based version were strongest in amygdala (AMY) and anterior insula (aINS, significant across analyses methods) and may most likely indicate emotional processes. More closely related to reward processing, we found differential involvement of the ventral tegmental (VTA) area and the substantia nigra (SNr) when comparing the game-based and the non-game-based task. In the following, we discuss these findings in more detail, starting with subcortical and then proceeding to cortical areas.

4.1. Subcortical processing of emotions and reward in game-based learning

In the MVPA, we observed neural activation patterns in the amygdala (AMY) to successfully (~64% accuracy) differentiate between feedback episodes in the game-based and non-game-based version of the learning task. This substantiated relatively stronger neural activation for game-based feedback compared to non-game-based feedback observed in our univariate analysis and indicates differential emotional processing for the two task versions within the same participants. Similarly, we found significantly distinguishable activation patterns along with strong activation differences in the anterior insula (aINS). For both brain areas, these findings are well in line with the literature on their involvement in emotional processing, such as their responsiveness to emotional stimuli (Phan et al., 2002), the experience of emotions (Vartanian & Skov, 2014) or reward (amygdala (AMY) only; Oldham et al., 2018). Stronger activation of the anterior insula (aINS) for the game-based task version might also be attributed to the experience of social emotions elicited, for instance, by the (e.g. joyful or crying) dog-avatar. We consider the observed systematic differences in the involvement of both the amygdala (AMY) and the anterior insula (aINS) as critical indicators, because both structures are assumed highly interconnected hubs and may promote the integration of information across several domains in the brain. The amygdala (AMY) system has been associated with the evaluative and expression dimension of emotions (Pessoa, 2017). The insula (INS) integrates perceptions, emotions, thoughts and plans (Kurth et al., 2010). Potential motor responses in subcortical regions (e.g. with the amygdala (AMY) as part of the basal ganglia), cannot explain these results because motor properties of both tasks were comparable and we controlled for button presses in the analyses.

Activation patterns for the putamen (PUT), a striatal area, also indicated stronger activation in the game-based version of the learning task compared with the non-game-based version. In line with previous evidence, we suggest that this reflects putamen's general involvement in reward processes (Silverman et al., 2015) or even more specifically, its role in learning reward-action correspondences (Cox & Witten, 2019). Another more content-wise interpretation assumes activation of striatal areas to be suppressed during winning and losing situations in active gaming (Kätsyri et al., 2013). However, this would be contrary to our results as observed for the putamen (PUT). Previous studies also suggested that the ventral striatopallidum (VSP), to which the putamen (PUT) belongs, links motivation to behavior (Waraczynski, 2006).

Unfortunately, results from other brain areas considered in our analysis and part of the striatum/VSP, such as the caudate nucleus (CAU), nucleus accumbens (NAC) and the ventral pallidum cannot dissolve this contradiction. While the MVPA indicated very well distinguishable activation patterns for the caudate nucleus (CAU), no significant activation differences were observed in the univariate analysis. In addition, neither significant activation differences nor differential activation patterns were decoded for the nucleus accumbens (NAC) and the ventral pallidum (VeP). In conclusion, neither the motivation-to-behavior link assumption nor the suppression during active gaming suggestion was corroborated by our results.

Another possible explanation might be that on the neurofunctional level, 'liking' reactions (e.g. experiences of pleasure) are specifically associated with only a few subcortical regions, so called hedonic hotspots, such as the nucleus accumbens (NAC) and ventral pallidum (VeP) (Berridge & Kringelbach, 2013). Although differential MVPA results for nucleus accumbens (NAC) and ventral pallidum (VeP) were not significant against the final z-threshold, the game/non-game-based version was identified with over 60% accuracy and a z-score of 1.88 on average. This indicates that at least a non-neglectable proportion of participants showed systematic differences in activation patterns for the game-based vs. non-game-based version of the task in this brain area. This interpretation also matches the significant advantage for the game-based task with respect to higher stimulation, novelty, and attractiveness, as reported in the UEQ. Statistical insignificance for the neurofunctional results in this case may rather be the consequence of our conservative group-level analysis.

Importantly, the ventral striatum was observed to respond selectively to positive vs negative feedback in game-based contexts (Howard-Jones et al., 2016). As our paradigm did not compare positive and negative feedback but included both in a joint analysis, this might contribute to the near threshold results for nucleus accumbens (NAC). While by far most items (>90%) were solved correctly, rare negative feedback may have introduced additional variance. Furthermore, nucleus accumbens (NAC) may be particularly sensitive to rewards during reward anticipation (Knutson et al., 2001), which was not considered in this study. This might have reduced discriminability of our results for this particular area.

Additionally, neuronal correlates of experiencing pleasure should be distinguished for causation (associated with subcortical areas) and representation (associated with prefrontal areas) which reflect to some degree separate neuropsychological functions (Berridge & Kringelbach, 2013). Specifically, only on a representation level, neuronal correlates of experiencing pleasure were observed for the game-based task version (see next paragraph).

4.2. Cortical processing of emotions and motivation in game-based learning

Important cortical areas contributing to the emotional processing such as the frontal orbital cortex (foC) (Pessoa, 2008) showed significantly different activation patterns for the game-based as compared to the non-game-based version of the learning task for the majority of our participants. In fact, the frontal orbital cortex (foC) showed one of the most differential patterns within our selection of ROIs (~68% classification accuracy). Importantly, this validated tendencies towards stronger activation for the game-based version as observed in the univariate analysis. This is well in line with the literature, as the frontal orbital cortex (foC) has been associated with reward outcome (X. Liu et al., 2011), in particular related to secondary rewards (Kätsyri et al., 2013). Moreover, representation of pleasure experiences seems to imply a major involvement of the frontal orbital cortex (foC) (Berridge & Kringelbach, 2013) whereas more medial subregions might be involved in monitoring learning as well as memory of reward values (Kringelbach & Rolls, 2004).

There were also significantly different patterns of activation for the frontal medial cortex (fmC). Importantly, however, this was the only ROI for which we observed a tendency towards increased activation for the non-game-based task version. This seems intriguing because limbic areas such as the frontal orbital cortex (foC) and frontal medial cortex (fmC) share their involvement in emotion processing and long-term memory (Barbas, 2000) and, together with the amygdala (AMY), were suggested to mediate stimulus-reward learning (Rudebeck et al., 2017). Conversely, medial prefrontal areas tend to show stronger activation during resting states (e.g. associated with mind-wandering) while decreasing activation in these areas may reflect cognitive processing coupled with a participant's emotional state (Raichle et al., 2001). Another perspective on the frontal medial cortex (fmC) is its potential role in motivational control, the flexible adaptation of resources to, for instance, a particularly challenging task (Summerfield & Koechlin, 2009). Under the premise that the non-game-based version is by default the more tedious and less engaging version of the task, maintaining adequate performance requires more effort in terms of motivational control and may thus lead to a stronger response of frontal medial cortex (fmC) compared to more intrinsic motivational states in the game based environment (Loderer et al., 2020). Extrinsically motivated situations, as suspected in the non-game-based environment, may in turn lead to an increase of effort to avoid failure (Loderer et al., 2018).

While learning stays largely intact, memory is traded for higher precision of single unit processing (Spachtholz et al., 2014). Eventually, such an effect may be reflected by the small but systematically higher estimation accuracy of participants solving the non-game-based version of the task. However, another explanation might be that the game-based version and the used game elements caused reduced estimation accuracy by distracting learners. In particular, in the domain of multimedia learning it has been argued that additional irrelevant elements included to instructional material may distract learners' attention away from central features of a task. This effect is often referred to as the seductive details effect (for a review see Rey, 2012; but see also Ninaus et al., 2020). One may also speculate, that the avatar in the game-based version (i.e. the dog) changed response behavior slightly. Maybe some participants placed the dog with his (front) paws or even the face on the estimated location rather than relying on the vertical indication line placed under the dog's centre (see Fig. 1). Eventually, we cannot exclude the possibility of a potential seductive details effect in our study or that in game-based learning, increased enjoyment might be traded for less accurate responses (Greipl et al., 2019), which need to be studied more systematically in the future.

4.3. Emotion and reward processing across the brain

MVPA indicated differential activation for both tasks in the anterior cingulate cortex (aCC), however only marginally increased relative activation for the game-based version of the task. In addition to its critical involvement in reward (Silverman et al., 2015) and emotion processing (Pessoa, 2008) in general, the anterior cingulate cortex (aCC) makes up a vital part of the so-called incentive motivational system (Berridge, 2004). Its recruitment during feedback episodes is therefore largely concordant with previous studies.

For the posterior cingulate cortex (pCC) there was an even clearer differential pattern of activations as well as significantly increased relative activation for the game as compared to the non-game-based version of the task. In addition to reward processing, the posterior part of the cingulate cortex (pCC) may reflect experiences of positive valence and also was observed to contribute to episodic memory processes (Silverman et al., 2015). Results from both anterior and posterior cingulate cortices (aCC/pCC) show that a substantial part of the structures relevant for reward processing in the brain was specifically recruited in the game-based tasks.

Finally, the hippocampus (HIP) showed significantly different patterns of activation for the game and the non-game-based task in the MVPA along with relative activations tending to be more pronounced in the game-based task. Hippocampus (HIP) belongs to extended parts of brain structures involved in emotion processing (Pessoa, 2008), and is associated with emotional behavior (Toyoda et al., 2011), mediates the encoding of salient stimuli together with the amygdala (Kensinger & Corkin, 2004), and is, if emotions are involved, interacting with the amygdala during formation of memory representations (Phelps, 2004). Although we cannot draw direct inferences on memory processes from the current study, the Hippocampus (HIP) is in the line-up of regions that showed involvement convergent with expectations.

4.4. Limitations & considerations

The challenge of the current study was to find a balance between preserving the game-based emotional experience and establishing a valid fMRI design. One consideration in this vein was examining more specific emotions such as surprise, confusion or boredom. However, implementing this in the experiment would have made the gaming experience even more difficult to preserve. The procedure would have had to be frequently interrupted in order to survey the participants about their current affective state. Keeping in mind that the currently employed game is set up to provide a genuine, albeit rather short-lived experience, an in-depth approach to, for instance, more complex (academic) emotions (e.g. Pekrun et al., 2002) was beyond the scope of this study. Furthermore, identifying such more specific emotional experience using fMRI would have been challenging given recent results of a meta-analysis by Lindquist et al. (2016).

As a potential limitation of the current study, it should be considered that brain areas associated with reward processing seem to be recruited differentially during reward anticipation and reward outcome (Oldham et al., 2018). Only the latter was addressed specifically in the present study. During reward outcome, increased activation was observed in the ventral striatum, the foC/ventral medial prefrontal cortex (vmPFC) and the posterior cingulate cortex (pCC), whereas striatal areas, insula (INS) and amygdala (AMY) may rather be associated with reward anticipation (Oldham et al., 2018). Future studies should, where possible, include both anticipatory and outcome phases in their analyses, especially when learning environments critically rely on feedback mechanisms. Also, because of overall good performance of participants on the fraction estimation task negative feedback was rare and not sufficiently represented to be analysed specifically or separately for positive/negative feedback. Nevertheless, it would be desirable to address this aspect more explicitly in future studies.

Moreover, we want to note that signal change values indicated an overall pattern of negative activations in all our ROIs. Similar phenomena during active gameplay were present in previous studies, for instance in which winning and losing situations during active gaming lead to similar activation patterns in striatal areas (Kätsyri et al., 2013). The authors explained this by the fact that in an active gaming scenario, activation of the striatum may be tonic and stays on an elevated level. The feedback episode evaluated in the current study may therefore represent a break, for instance from being engaged with the task at hand, from which neural activation then may come back closer to baseline level. However, this is an issue we cannot address directly because the raw BOLD signal from two separate scanning sessions is essentially arbitrary and only allows interpretation of relative activation differences.

5. Conclusion

Our results provide clear evidence that neurofunctional correlates of emotional, reward and even motivational processing differ significantly for the game as compared to the non-game-based version of the task. Pattern analysis revealed highly significant differential contributions of brain areas including the amygdala (AMY), the anterior insula (aIN), posterior cingulate cortex (pCC), putamen (PUT), substantia nigra (pars reticulata, SNr), ventral tegmental area (VTA), hippocampus (HIP), anterior cingulate cortex (aCC), frontal medial/orbital cortex (fmC/foC) and caudate nucleus (CAU). Additionally, for most of these areas there also were significant activation differences in terms of increased activation in the game-based as compared to the non-game-based version of the task. The results imply that potential advantages of game-based learning may indeed not only be grounded in its more rewarding, but also in its emotionally engaging nature.

Together with the reciprocity between emotion and cognition, our data indicate that enriching a learning environment by game elements is not inevitably distractive, as proposed in some previous studies (Mayer & Moreno, 2003). Instead, the present study demonstrates that game-based learning tasks and games for learning in general should not be regarded as tasks that have only been injected with fun elements, but as dedicated learning tools which can invigorate the learning experience.

Author contributions

S.G.: study design, data acquisition, analysis, interpretation, software implementation, original draft preparation, manuscript preparation & revision. E.K.: study design, interpretation, manuscript preparation. A.L.: software implementation. K.K. software implementation, manuscript revision. K.M.: study design, data interpretation, manuscript preparation & revision. H.-O.K.: manuscript revision. J.Ba.: data acquisition, manuscript revision. J.Bl.: data acquisition, manuscript revision. M.N.: study design, analysis, interpretation, original draft preparation, manuscript preparation & revision, supervision, funding acquisition. All authors approved the final manuscript.

Declaration of competing interest

The authors declare no competing interests.

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