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Research article

The impact of wellness on neural learning systems

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ABSTRACT

Over the past 20 years there has been an increasing push for people to achieve or maintain "wellness" - a state in which one has not only physical but also mental and social well-being. While it may seem obvious that maintaining a state of wellness is beneficial, little research has been done to probe how maintaining a state of wellness impacts our brain. Here, we specifically examined the impact of wellness on a neural system within the medial-frontal cortex responsible for human reinforcement learning. Sixty-two undergraduate students completed the Perceived Wellness Survey after which they completed a computer-based learnable gambling game while electroencephalographic data were recorded. Within the game, participants were presented with a series of choices that either led to financial gains or losses. An analysis of our behavioral data indicated that participants were able to learn the underlying structure of the gambling game given that we observed improvements in performance. Concurrent with this, we observed an electroencephalographic response evoked by the evaluation of gambling outcomes - the reward positivity. Importantly, we found significant relationships between several aspects of wellness and the amplitude of the reward positivity. Given that the reward positivity is thought to reflect the function of a reinforcement learning system within the medial-frontal cortex, our results suggest that wellness impacts neural function – in this instance one of the systems responsible for human learning.

1. Introduction

Health science has begun transitioning from a focus on pathogenic health (disease-focused) to a focus on salutogenic wellness (health-promoting). In general, wellness begets positive perceptions of the self and life events, resilience to negative experiences, and even resilience to physical ailments [1–10]. Typically, the broad construct of wellness is thought to have component dimensions: psychological, emotional, social, physical, spiritual, and intellectual (see Adams [11] for a full review of each of these component dimensions; also see 12–15). In a systematic review, Strout and Howard [14] reported that high levels of wellness in the intellectual, physical, social, and emotional dimensions were related to improved memory, reasoning, attention, executive control, language, processing speed, and global cognitive performance. Indeed, a growing body of work consistently reports positive relationships between wellness and various aspects of cognitive function [15–18]. Of interest here, is the relationship between wellness and a specific aspect of cognitive function – learning. For instance, Yu et al. [20] reported a positive relationship between wellness and academic achievement after examining 434 students over several years of study. Other work by Eisenberg et al. [21] and Stamp et al. [22] supports this and also highlights that having a state of wellness has a positive impact on learning.

A key aspect of learning is reward processing – our ability to evaluate outcomes and adapt behavior accordingly. One way to probe human learning is to examine changes in the reward positivity – a component of the human event-related brain potential (ERP) sensitive to performance feedback [23,24]. A growing body of evidence suggests that the reward positivity reflects a reinforcement learning prediction error – a signal computed as the difference between an expectation and an outcome [25,26]. Experimental evidence links the reward positivity to learning, as a number of studies have found concomitant relationships between changes in the amplitude of this ERP component and behavior [27–29]. In terms of an underlying mechanism, changes in the amplitude of the reward positivity have been linked to phasic changes in dopamine (see Schultz [30] for a review) reflective of the computation and conveyance of reinforcement learning prediction errors [25,30]. Interestingly, there is also a body of work that links wellness to dopamine; greater tonic levels of dopamine have been associated with greater wellness and vice versa [15,36,39].

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Table 1
Normative comparisons of past research using the perceived wellness questionnaire. N (female) = sample size with how many females in the corresponding study, PWS = perceived wellness score.

	Population	N (Female)	Mean Age	Mean PWS Score
Adams et al. (1997)	Corporate Workers Sample 1	393 (153)	41.10	15.91
	Corporate Workers Sample 2	53 (47)	34.34	15.35
	Undergraduate Students	112 (91)	23.15	16.49
Bezner, & Hunter (2001)	Patients with Traumatic Brain Injury	49 (6)	32.10	15.99
Ketz & Israel (2001)	Bisexual Females	69 (69)	27.17	13.74
Naugle et al. (2013)	Athletic Trainers	390 (158)	35.56	16.55

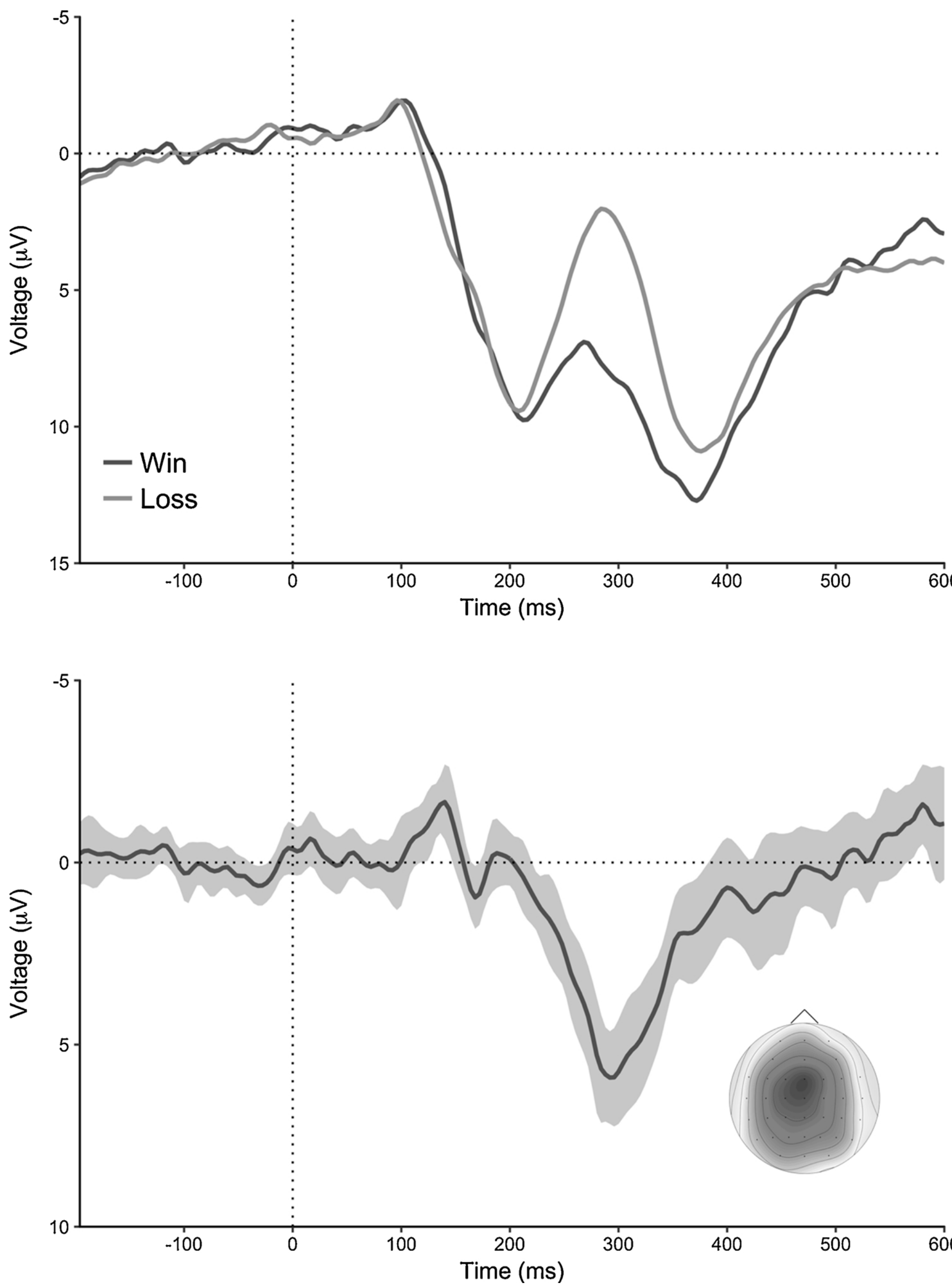

Fig. 1. Conditional and difference ERP waveforms showing the reward positivity. Top: conditional waveforms, bottom: difference waveforms with 95% confidence intervals and an inset showing the topography of the reward positivity.

Given the aforementioned impact of wellness on cognitive function and hypotheses that dopamine plays a role in both wellness and reinforcement learning, it seems reasonable to expect that wellness, or lack of wellness, would impact neural learning systems. In the present study, we examined the relationship between wellness and a neural signal reflective of a reinforcement learning system within the human medial-frontal cortex – the reward positivity. First, participants completed a validated survey to assess current level of wellness [26,31,32].

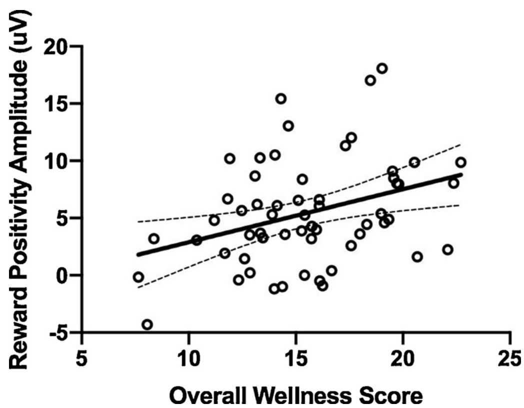

Fig. 2. Scatterplot of the relationship between the overall wellness scores and reward positivity amplitude. The solid grey line represents a linear regression.

Table 2

Correlation matrix of wellness, the six dimensions of wellness, and the reward positivity. WELL = wellness, PSYC = psychological dimension, EMOT = emotional dimension, SOCI = social dimension, PHYS = physical dimension, SPIR = spiritual dimension, INTE = intellectual dimension, Reward positivity = reward positivity. Each cell is colour coded based on the strength of correlation: dark grey = strong correlation, grey = medium correlation, light grey = weak correlation.

	PSYC	EMOT	SOCI	PHYS	SPIR	INTE	WELL
EMOT	.60						
SOCI	.42	.45					
PHYS	.41	.41	.44				
SPIR	.61	.54	.43	.30			
INTE	.42	.50	.20	.18	.53		
WELL	.78	.81	.69	.66	.77	.63	
Reward positivity	.23	.32	.31	.18	.32	.16	.35

Next, participants completed a gambling task while electroencephalographic (EEG) data were recorded. By recording EEG data, we were able to quantify the reward positivity to examine a potential relationship between this component and wellness. Our primary hypothesis was that we would observe a relationship between wellness and the amplitude of the reward positivity. Importantly, if observed, this result would help establish a neural marker to examine the relationship between wellness and cognition in addition to providing insight into the impact of wellness on human learning [28]. In terms the six component constructs of wellness (psychological, emotional, social, physical, spiritual, intellectual) we did not have any specific hypotheses perse.

2. Methods and materials

2.1. Participants

Sixty-two undergraduate students (47 females, mean age: 20.4 [CI: 19.8 21.0]) from the University of Victoria participated in the experiment. Four participants were removed from analysis - two were removed for having outlying data (as determined by an analysis of regression residuals) and two were removed due to missing or incomplete EEG data yielding a sample size of fifty-eight participants for further analysis. All participants had normal or corrected-to-normal vision, no known neurological impairments, and were recruited through voluntary extra course credit in a psychology course. Written informed consent, approved by the Human Research Ethics Board at the University of Victoria (16–428), was obtained.

2.2. Apparatus and procedure

Participants sat in a sound dampened room, in front of a 19″ LCD computer monitor. Prior to the start of the EEG task, participants completed wellness the Perceived Wellness Survey [11]. Following completion of the survey, participants completed a reward-learning task while EEG data were recorded (ActiCHamp, Brainproducts GmbH, Munich, Germany). Experimental tasks were coded in MATLAB programming environment (Version 8.6, Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox extension [33].

Each trial of the reward-learning task started with participants viewing a black fixation cross against a dark grey background cross for 300–500 ms. Following this, two coloured squares appeared, one on either side of the fixation cross. Next, participants were prompted to select one of the coloured squares using a standard USB Gamepad. Following the selection of a square, the squares disappeared and the black fixation cross reappeared for 300–500 ms. Subsequently, a feedback stimulus ("WIN" for wins, "LOSS" for losses) was shown for 1000 ms reflecting the outcome of the participants gambling choice. Unbeknownst to participants, selection of one of the coloured squares resulted in more frequent wins than the other – a 60% versus 10% likelihood of winning. Given that the win percentage of one of the coloured squares was better than the other, the task was learnable – within each block of trials one would expect to see participants begin to select the "better" (60%) colour more frequently than the "worse" (10%) colour. After each outcome was presented, the next experimental trial began immediately following the offset of feedback stimulus. The location of each coloured square (left, right) was randomly determined each trial thus making colour and not location the key feature to learn as the win/loss ratio to colour relationship remained constant for each block of 20 trials. Participants completed five blocks of trials and unique square colours were used for each block.

2.3. Behavioural data

Prior to performing the experimental task, participants completed the Perceived Wellness Survey (PWS) developed by Adams et al. [11] This survey consists of 36 questions assessing six wellness dimensions and has been shown to be a highly reliable measure of wellness [11,31,32]. Wellness scores were evaluated according to the methods described in Adams et al [11]. Briefly, Perceived Wellness Survey incorporates a measure of magnitude for each dimension of wellness and a measure of balance across dimensions. Both magnitude and balance contribute equally to the overall 'wellness score' which is simply the sum of the subscale means divided by the sum of the standard deviations among the subscale means and a corrective factor of 1.25 used to prevent a standard deviation of 0 in the denominator.

Throughout the gambling task, we recorded accuracy rates to ensure participants learned to discern the more rewarding square from the less rewarding square. In other words, if participants learned to discern the two squares we would predict that the percent selection of the optimal square- the one that won 60% of the time - would increase within each block of trials. To demonstrate this, we directly compared the mean accuracy rate for each participant between the early (trials 1 to 10) and late (trials 11 to 20) trials of each experimental block of trials.

2.4. Electroencephalographic data

EEG data were recorded using Brain Vision Recorder software (Version 1.21, Brainproducts, GmbH, Munich, Germany) via 64 electrodes that were attached to a fitted cap, using a modified version of the standard 10–20 layout (see http://www.neuroeconlab.com/electrode-configuration.html). Once fitted on the cap, electrodes were initially referenced to a common ground. Average electrode impedances were kept below 20 kΩ. EEG data were sampled at 500 Hz, amplified (ActiCHamp, Version 2.0, Brain Products GmbH, Munich, Germany), and filtered through an anti-aliasing low-pass filter of 8 kHz. A DATAPixx stimulus unit was used (VPixx, Vision Science Solutions, Quebec, Canada) to ensure temporal coincidence of event-markers with experimental stimuli.

Data were processed offline with Brain Vision Analyzer 2 software (Version 2.1.1, Brain Products, GmbH, Munich, Germany) using methods previously employed by our laboratory (see http://www.neuroeconlab.com/data-analysis.html). First, excessively noisy, flat, or faulty electrodes were removed from analysis. The EEG data were then re-referenced to an average linked mastoid reference and were then filtered using a dual pass Butterworth filter with a passband of 0.1–30 Hz in addition to a 60 Hz notch filter. To facilitate independent component analysis (ICA), epochs encompassing the onset of each event of interest (the onset of win and loss feedback stimuli: 1000 ms before to 2000 ms after) were extracted from the continuous EEG. Following this initial segmentation, ICA and ICA back transformation was used to correct ocular artifacts [34,35]. Data were reconstructed after ICA using the remaining independent components and any channels that were removed initially were interpolated using the method of spherical splines. New, shorter epochs were then constructed; from 200 ms before to 600 ms after the onset of each event of interest. Following this, all segments were baseline corrected using the 200 ms window preceding stimulus onset. Finally, all segments were submitted to an artifact rejection algorithm that marked and removed segments that had gradients of greater than 10 μV/ms and/or a 100 μV absolute within segment difference (mean percent of trials rejected: 21% [CI: 15% 28%]).

ERP waveforms were then created by averaging the epoched EEG data for each channel and participant. Subsequently, difference waveforms were also created for each participant by subtracting the average loss waveforms from the average win waveforms. Grand average conditional and difference waveforms were created by averaging corresponding ERPs across all participants. The ERP component of interest, the reward positivity, was quantified as follows. First, the point of maximal deflection from zero μV on the grand average difference waveform in the time range of the reward positivity (250–350 ms; [23]) was identified yielding the grand average difference peak time. Next, we confirmed that this maximal deflection was on Channel FCz – the channel identified for quantification of the reward positivity in previous literature and by visual inspection on our data [23,25,36,37]. Having met these antecedent conditions of the reward positivity, we statistically quantified the component by computing the mean voltage +/− 25 ms of the grand average difference peak time (300 ms) on the individual difference waveforms for channel FCz for each participant.

2.5. Statistical analysis

We assessed the reliability of the Perceived Wellness Questionnaire with Cronbach's alpha. To gauge learning, we used a dependent samples *t*-test to compare the mean early and late accuracies. To demonstrate that feedback elicited a reward positivity, we used a single sample *t*-test to compare reward positivity peak amplitudes to zero. The logic of this test is straightforward, if no reward positivity was present (i.e., there was no difference between win and loss waveforms), then the peak amplitude values we computed should have a Gaussian distribution around zero. To examine the relationship between the reward positivity and wellness, we calculated Pearson's correlation coefficients between the amplitude of the reward positivity and overall wellness. We also calculated Pearson's correlation coefficients between reward positivity amplitude and each of the six individual dimensions of wellness.

3. Results

Reliability of the Perceived Wellness Questionnaire was established as we computed a Cronbach's alpha score of 0.90 (psychological: .59, emotional: .79, social: .71, physical: .79, spiritual: .71, intelligence: .68). Across all participants, the mean wellness score was 15.5 [CI: 14.6 16.3]. To afford normative comparisons with other work, we have summarized several studies that also report mean wellness scores in Table 1. In terms of task performance, we found that accuracy rates increased from the early to the late portion of each block, $t(57) = 2.37$, $p < 0.05$ demonstrating that participants learned to select the optimal gamble. Examination of our electroencephalographic data revealed that performance feedback elicited a robust reward positivity with a timing and scalp topography consistent with previous literature (Fig. 1: $t(57) = 8.6$, $p < .001$) [24].

Our analysis focused on an examination of the relationship between scores on the Perceived Wellness Survey and the amplitude of the reward positivity. In terms of an overall effect, we observed a medium strength correlation between overall perceived wellness and the amplitude of the reward positivity (see Fig. 2: $r(57) = .35$, $p < 0.01$) [41]. To affirm this result, a median split comparison revealed that the amplitude of the reward positivity was greater for participants with high wellness (18.2 [CI: 17.4 19.0]) than for those with low wellness (12.8 [CI: 12.0 13.5]), $t(57) = 2.1$, $p < 0.05$ (high 8.7 μV [7.5 μV 9.9 μV], low 1.5 μV [0.7 μV 2.4 μV]). Examination of the relationship between each of the six individual dimensions of wellness and the amplitude of the reward positivity revealed medium strength correlations with the emotional ($r(57) = .324$, $p < 0.01$), social ($r(57) = .314$, $p < 0.01$), and spiritual dimensions of wellness ($r(57) = .317$, $p < 0.01$) [38]. We also observed small correlations between the amplitude of the reward positivity and the psychological ($r(57) = 0.227$, p = 0.059), physical ($r(57) = .178$, p = 0.225), and intelligence ($r(57) = 0.159$, p = 0.286) dimensions of wellness [38]. It is worth noting that this pattern of results did not differ with the two outliers included in our analysis. Specifically, we still found significant medium strength relationships between the reward positivity and the emotional, social, spiritual dimensions of wellness and overall wellness (r's = 0.293, 0.286, 0.286, 0.321 respectively, all p's < 0.05) and weak relationships non-significant between the reward positivity and the psychological, physical, and intelligence dimensions of wellness (r's = 0.214, 0.186, 0.128 respectively). For an overview of all correlation scores between variables see Table 2.

4. Discussion

In the present study, we demonstrate a relationship between the amplitude of the reward positivity – a neural response thought to reflect a learning system within the human medial-frontal cortex – and wellness. Specifically, we observed a positive correlation between overall wellness and the amplitude of the reward positivity. Supporting this, a median split analysis affirmed that the amplitude of the reward positivity was greater for people who reported higher overall wellness. Interestingly, an examination of the relationship between the amplitude of the reward positivity and six individual dimensions of wellness revealed relationships between the emotional, social, and spiritual dimensions of wellness and the amplitude of the reward positivity. We also observed small correlations between the psychological, physical, and intellectual dimensions of wellness and the amplitude of the reward positivity.

What is the mechanism by which wellness impacts the reward positivity? First, there is evidence demonstrating that greater wellness is associated with higher levels of dopamine within the brain [19,36,39]. Second, a key account of the reward positivity links changes in the component amplitude to phasic changes in dopamine [24]. Several sources support the dopamine-reward positivity connection. For example, studies using functional magnetic resonance imaging indicate that reward processing within the medial-frontal cortex and specifically anterior cingulate cortex parallels the prediction error like activity seen in the dopaminergic response in monkey [40,41], and other related work has shown that dopamine release timing coincides with reward positivity latency [24,25,37,42]. Finally, dopamine agonists (e.g., morphine), cocaine (reuptake inhibition) and amphetamines (increase dopamine release) enhance dopaminergic activity and increase positive affect [43]. As such, given the relationship between wellness and dopamine and the relationship between the reward positivity and dopamine there is a common neural mechanism linking the two.

Given the present observation that wellness is positively correlated with the amplitude of the reward positivity, and thus potentially with learning, there are implications of our result within educational contexts. Indeed, explicit learning, necessary to learn skills and acquire expertise in academic subjects, requires executive control [44] and it has been demonstrated that poor wellness impacts executive function [43]. With this in mind, there is a need to create interventions that promote the improvement of wellness leading to suitable learning environments and increased cognitive abilities [45,46]. Interestingly, there is evidence that improving an educational system will also increase wellness [45,46] thus creating a positive-feedback loop allowing improvements in any of these facets to improve our wellness, and in turn, improve learning [45,46]. Although our findings demonstrate a relationship between an ERP signal associated with human reinforcement learning and wellness, further research is necessary to fully understand how the dimensions of wellness impact neural function.

With this in mind, it is important to emphasize here that the primary findings are a series of correlations between wellness and the amplitude of the reward positivity. As noted above, it is possible that greater wellness stems from an increase in dopamine within the brain and as such the amplitude of the reward positivity is enhanced. However, given that we are unable to determine causality here it is important to recognize that the reverse could be true. An alternative explanation for our findings is that greater functional efficacy of the system that underlies the reward positivity could result in greater wellness. Another issue to consider here is that what we are actually measuring is perceived wellness and not wellness itself given that our wellness data comes from self-report. It is important to take this into account when examining our findings as it could be that the aforementioned links are only between perceived wellness and the reward positivity. Additionally, wellness is multi-faceted and influenced by other factors. Thus, the relationship we found between neural learning systems and wellness could also possibly be derived by a moderating factor. The current study only focused on investigating wellness, thus, we were not able to address whether there were any confounding factors that could explain our data. However, future research could address this by additionally collecting a myriad of other measures related to wellness. Another limitation to the current study is that we measured wellness only on one occasion. Future research could better define the relationship between wellness and neural learning systems by testing the same individuals multiple times. This would then be able to account for individual differences in both wellness and neural learning systems, revealing a more precise relationship between the two. A final caveat we would like to address is that here our study focused on undergraduate students in western North America. With this, it is difficult to determine how far our findings may generalize. It will be important for future research to address this by recruiting participants across populations and cultures.

5. Conclusions

In sum, here we demonstrate a relationship between wellness and the amplitude of the reward positivity. Given that higher levels of dopamine are thought to underlie greater wellness [43] and that there is a purported relationship between dopamine and the amplitude of the reward positivity [25], our findings suggest a potential functional mechanism by which wellness could impact a neural learning system. Importantly, our results speak to the importance of wellness in learning and in emphasizing wellness in all educational contexts.

Declaration of Competing Interest

The Authors declare that there is no conflict of interest.

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