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Attentional Bias Pattern Recognition in Spiking Neural Networks from Spatio-Temporal EEG Data

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Abstract When facing with different marketing product features, consumers are unaware of the important role of external stimuli on their decision-making behaviour. Neuromarketing background suggested that consumers might be seduced by the attentional bias which can direct their decision. This study aims at modelling and visualisation of the brain activity patterns generated by marketing product features with respect to the spatio-temporal relationships between the continuous EEG data streams. This research utilises brain-like Spiking Neural Network (SNN) models for analysing spatio-temporal brain patterns generated by attentional bias. The model was applied to Electroencephalogram (EEG) data for investigating the effectiveness of attentional bias on consumer preference towards marketing stimuli. Our experimental results have shown that consumers were more likely to get distracted by product features that are related to their subconscious preferences. This paper proofs that consumers pay the highest attention to non-target stimuli when they were presented with attractive features. This study provided a proof of principle for the role of attentional bias on concern-related human preferences. It represents knowledge discovery in the prediction of consumer preferences in the field of neuromarketing. The SNN-based models performed superior not only in achieving a higher classification of EEG data related to different stimuli in comparison with

traditional methods, but it most importantly enables a better interpretation and understanding of underpinning brain functions against marketing stimuli.

Keywords Neuromarketing · Attentional bias · Consumer preferences · Decision making · NeuCube · Spiking neural networks · Spatio-temporal brain data

Introduction

In a decision-making study, there are several influential factors on human choice behaviour such as environment, society, and culture. that may provoke attentional bias which leads to certain decisions. Attentional bias [1] is described as human perception affected by concerned-related stimuli (distracting information which is irrelevant to the task) over other information. In the field of neuromarketing, consumers might be seduced by the attentional bias which can direct their preferences to particular products [1, 2]. Recent studies have shown that attentional bias could be simulated towards familiar marketing stimuli because consumers prefer to focus on what they already know at the expense of new information [2, 3].

“Branding” has been thought as a prevailing feature of a product, though the role of external stimuli might also provoke consumer attention. This is in line with the importance of concerned-related cues in particular stimuli. For instance, in research [4], EEG data has been used to investigate the functionality of occipito-temporal cortex in response to a concept-colour association task. The research suggested that colour features were vital external factors, by seducing consumer attention and affecting their decision.

In a marketing environment, the vital role of external stimuli on buying behaviour is usually obscure for consumers [1, 2] that is why researchers are not able to examine all possible

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outcomes to assess a choice behaviour when using questionnaires or other discourse data.

Recently, researchers in the field of marketing and advertising have sought the aid of neuroscience methods as a suitable way to understand the foundations of market behaviour [5]. From the psychological point of view, several types of cognitive biases occur due to attentional bias, which refers to paying increased attention to certain stimuli. Therefore, it is important to analyse the behavioural consequences of these psychological biases as they might severely influence consumer choices.

Most of the studies on attentional bias were in counselling with psychological problems, particularly anxiety depression and addiction. People with anxiety have an attentional bias towards threat; those who are depressed tend to have a strong attentional bias towards negativity, and addicts have an attentional bias towards terms or concepts related to drugs. Researchers also studied the behaviour of addicted people towards drug-related cues in comparison with non-drug-related ones [6]. Evidence has exposed that addicted people to substances (e.g. alcohol and opiate) pay significantly greater attention to drug stimuli compared to a control group [6–8]. Positive correlation of attentional bias with concerned-related stimuli can be considered as an effective factor for prediction of consumer preference and choice behaviour.

The human brain performs as a complex information processing system which contains billions of neurons that communicate through their synapses. Thus far, several methods have been proposed for recording activities of such neurons to provide spatio-temporal brain data (STBD) for studying of human choice behaviour in the marketing environment. However, neural mechanisms that underpin the attentional bias have not yet been analysed in depth using traditional approaches, including multilayer perceptron (MLP), Support Vector Machine (SVM), and regression techniques.

To meaningfully interpret the underpinning of cognitive mechanisms in the brain, an appropriate methodology is required to sufficiently analyse the interaction and interrelationships between complex multivariate STBD.

In the brain, neurons are the fundamental processing elements which are interconnected and can exchange their information by means of electrical pulses (called spikes) that create a trajectory of sequential activities between spatially positioned neurons. Inspired by the structure of the brain neurons, artificial spiking neural networks (SNN) have been developed [9–11] as biologically plausible computational models that incorporate both temporal and spatial characteristics of data through portioning the models [12].

Electroencephalogram (EEG) is a kind of STBD, which measures the cortical activity elicited from the brain and it has long been used to analyse preference and decision-making [13–15]. For instance, research [16] used EEG data and identified that frontal and pre-frontal cerebral regions were mostly involved when people viewed enjoyable TV

commercials. The research also confirmed an unbalance between right and left hemispheres as various band frequencies were observed.

Now our study here represents a new approach, based on the NeuCube brain-like SNN architecture [17], to model and study the brain functional activities and the effects of attentional bias on consumers' decision. As represented in [18–22], the NeuCube enabled us to investigate the cognitive processes across different circumstances and individuals. In order to illustrate the NeuCube methodology, a case study of EEG has been used here to investigate the brain activity patterns in response to target and non-target stimuli.

This research includes the following objectives:

- a) To investigate the effect of consumer attentional bias on their preferences when facing with concerned-related marketing stimuli
- b) To create computational models from EEG data in order to detect the activated brain regions corresponding to attentional bias towards non-target stimuli in a distraction paradigm task;
- c) In particular, our experiments aim at modelling and understanding of the brain activity patterns generated by drink product features with respect to the spatio-temporal relationships between the continuous EEG data streams while the subjects were looking at (1) only brand name and (2) brands that come with a content (e.g. colour and design).

The current paper is structured based on the following sections: Section 2 illustrates our cognitive task and the acquisition of EEG data; Section 3 describes the method for EEG data modelling, learning and visualisation using the NeuCube architecture; Section 4 reports the experimental results; Section 5 represents the conclusion; and finally, figures and tables are presented.

Cognitive Task Description and EEG Data Acquisition

In this research, we used EEG data collected from nine male volunteers with the mean age of 36.40. All participants had normal vision with no neurological abnormalities. Prior to the EEG measuring, each participant was given a written consent form. They were informed that involvement is optional and they retain the right to withdraw their participation at any time. The data measuring procedure was accomplished in the KEDRI, "Knowledge Engineering and Discovery Research Institute", Auckland University of Technology, New Zealand.

To address the research goals, a cognitive task was designed according to the oddball paradigm [23, 24]. The task was constituted by a set of presentations of target vs non-target stimuli. In this task, the target stimulus study was a bottle of water. As the non-target stimuli set, different features of a drink, such as the

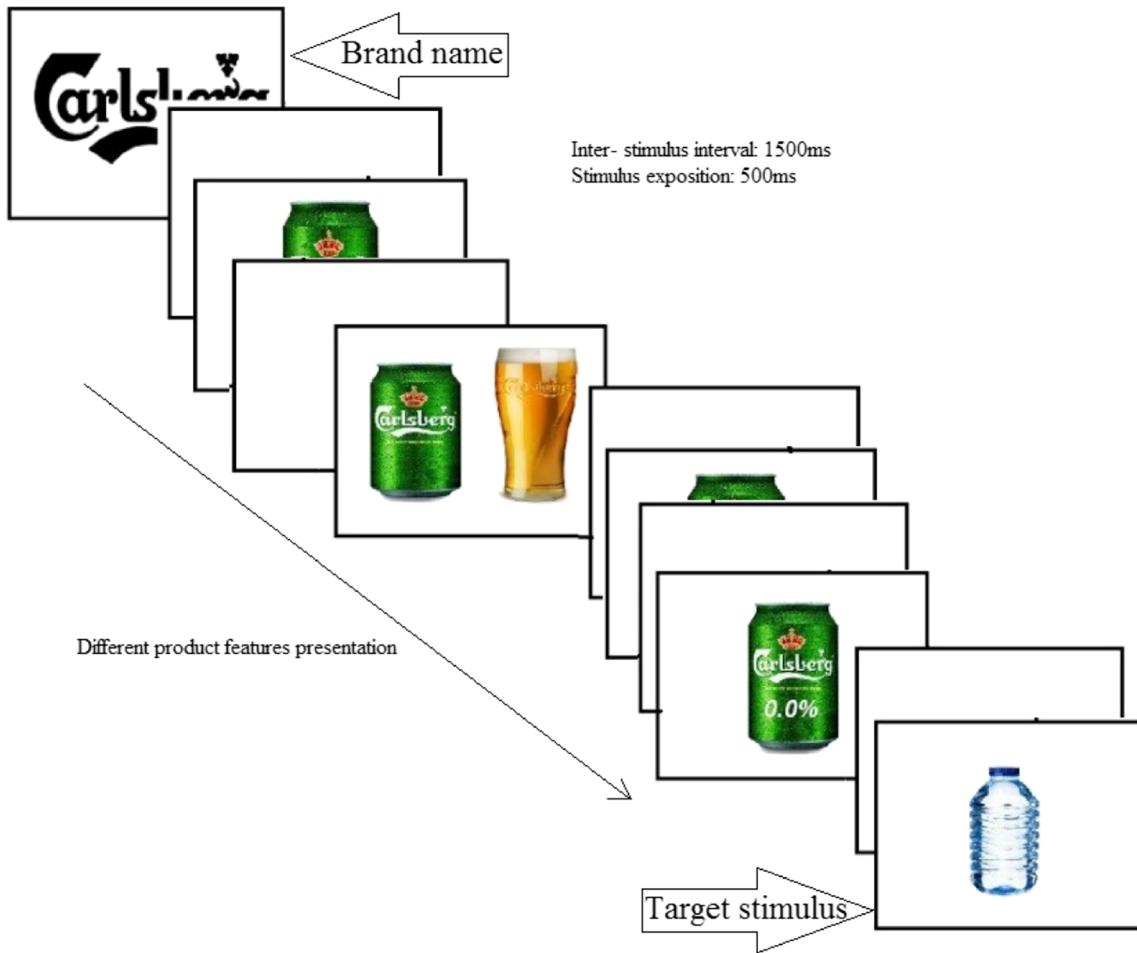


Fig. 1 Presentation of the designed mental task which is combination of a target stimulus (a bottle of water) and other different product features as the non-target stimuli. The exposition time for each stimulus is 500 ms and Inter stimulus interval 1500 ms.

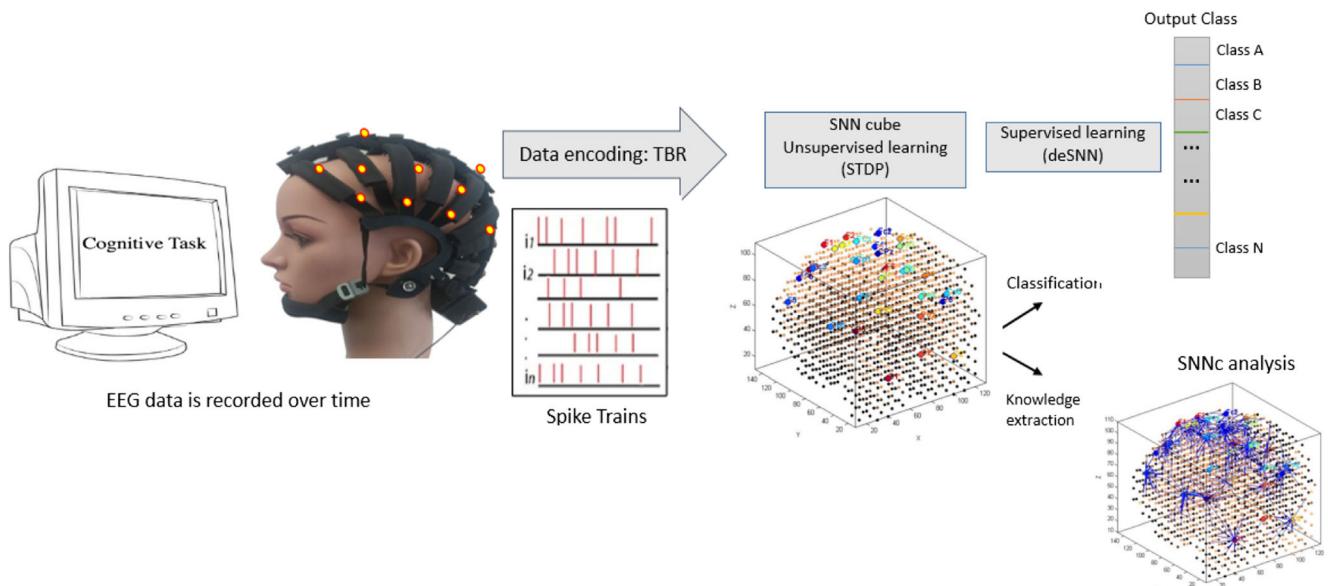


Fig. 2 Spatio-temporal brain data procedure using NeuCube framework, consisting of several steps: Input data encoding; 3D SNNc visualisation in unsupervised learning; classification/regression using supervised learning; model analysis and knowledge extraction

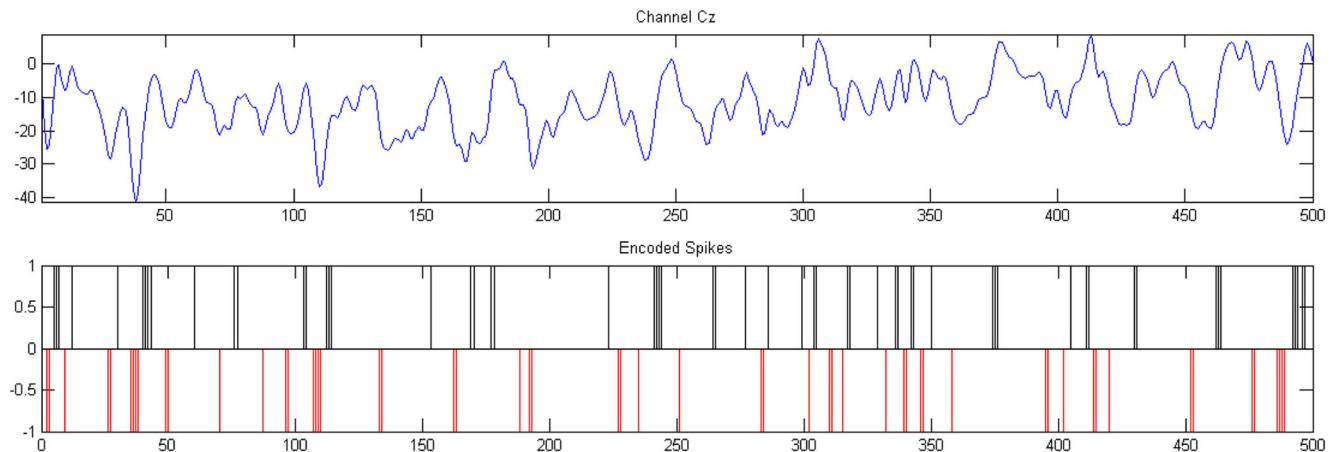


Fig. 3 Encoding EEG data of one channel (Cz), the first 500 data points, into sequence of spikes based on the TBR algorithm. Black lines corresponding to the positive spikes and red lines represent negative ones [20]

name of a brand or the brand name overlapped by contexts were used. During the task, subjects were requested to respond as soon as observing the target stimulus on screen by pressing the mouse button. The design of task is illustrated in Fig. 1.

Every stimulus had an exposition time of 500 ms. The inter stimulus interval (ISI) was assigned between 1300 and 1500 ms randomly. There was a total number of 66 presentations of the target stimulus, whereas 264 number of presentations for the non-target stimuli. While the task was displayed, concurrently event-related potentials (ERPs) were measured.

The EEG data collected from 32 electrodes positioned with respect to the standard “10–20” international location system, namely: AF3, AF4, F1, F2, F3, F4, F5, F6, FZ, FC3, FC1, FCZ, FC2, FC4, CP5, CP1, CPZ, CP2, CP6, P1, P2, P3, P4, P5, P6, PZ, POZ, PO3, PO4, O1, O2 and Oz. EEG data were recorded using (Cognionics Instruments, Dry EEG system) with 500 Hz of the sampling rate.

Method: Brain-like SNN Architecture NeuCube

In this study, a brain-like SNN methodology, called NeuCube, is used to build accurate models of EEG data to evaluate how such attentional bias can affect the consumer preferences. The NeuCube architecture consists of several main functional modules (illustrated in Fig. 2), including input encoding; mapping of a 3D SNN model and unsupervised learning; supervised learning for classification/regression; an optimisation procedure; and knowledge discovery and interpretation [17].

In the following sections, these modules will describe the methodology applied here.

STBD Encoding and Mapping

NeuCube supports different encoding methods with respect to the nature of STBD such as EEG and fMRI—a novel

approach has been introduced for fMRI data encoding in [25]. In the current paper, a threshold-based representation (TBR) method, which has been successfully applied to the artificial retina sensor [26], was applied to each EEG channel time series to encode it into a sequence of binary events, called spikes. In this technique, when the EEG signal alteration surpasses a pre-defined threshold, a spike generates. Finally, for each EEG channel, we obtained a train of positive spikes that represent the time-dependent positions of the ascending changes in signal. In addition to the positive spike train, a negative spike train is also generated per EEG channel that presents the positions of the descending changes.

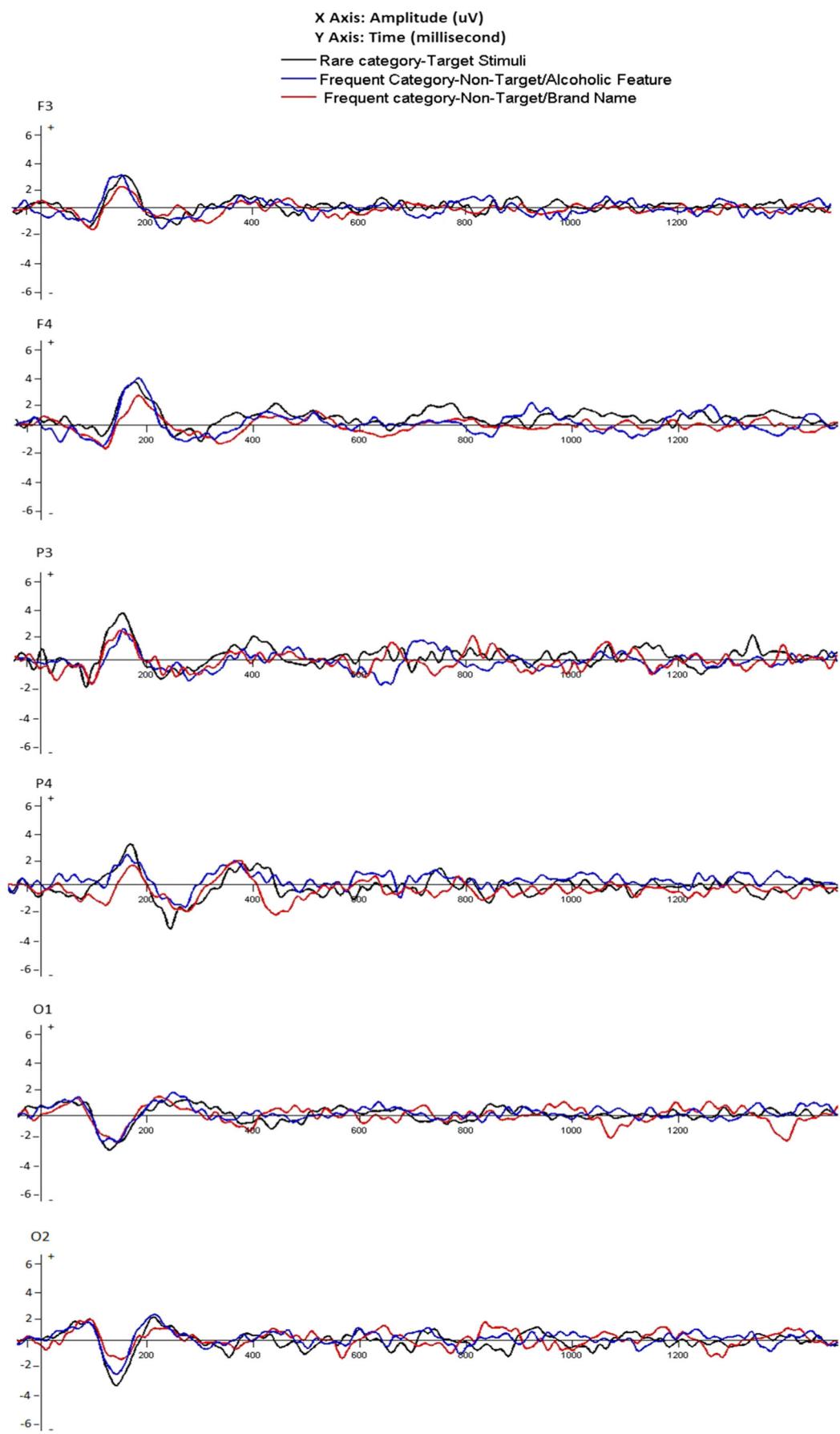
As an example, the TBR encoding method was applied to a time series of one EEG channel signal to encode it into a spike as shown in Fig. 3.

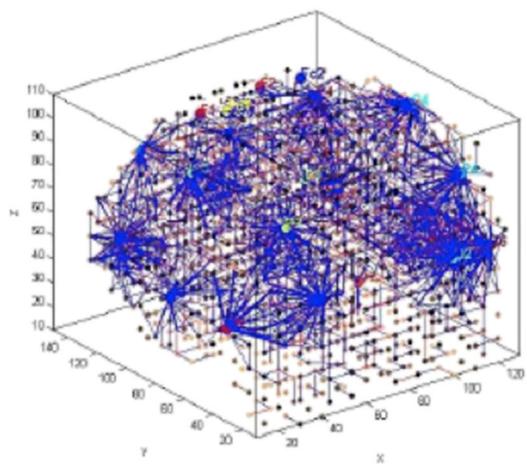
Unsupervised Learning in the 3D SNNc

SNNs rely on the timing of spikes for defining the network interconnections. The SNN principle differs from traditional neural networks; thus, it requires different learning rules. A model of a spiking neuron defines a computation that processes the incoming spikes and triggers firing on its output.

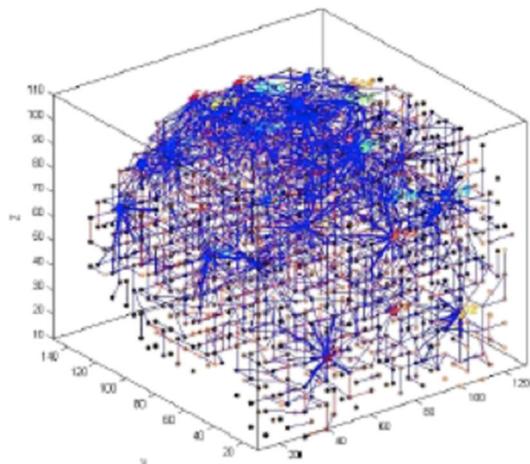
In the NeuCube-based SNN architecture, each neuron is a computational unit, which can be simulated by several models. A 3D SNN reservoir (called SNN cube or SNNc) can spatially map the brain templates, such as Talairach [27, 28]. The small-world connectivity rule [26] has been used here to establish the initial connection weights in the mapped SNNc. Then the initial connectivity is modified through unsupervised learning—spike-timing-dependent

Fig. 4 Grand average ERP waveforms of nine subjects across 1200-ms epoch after target versus non-target drink features stimuli presentation across six EEG channels (F3, F4, P3, P4, O1 and O2). Black line is target stimuli; blue line is non-target stimuli/alcoholic features; and the red line is non-target stimuli/brand name

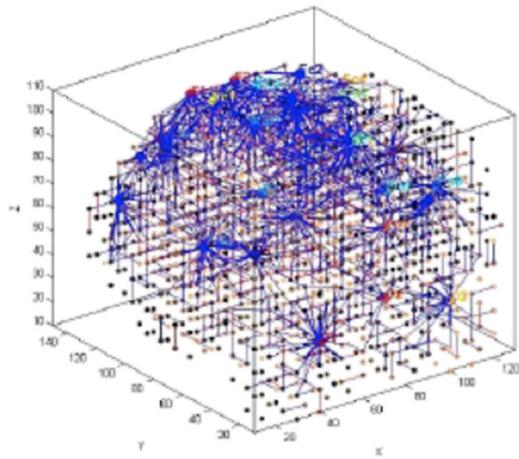




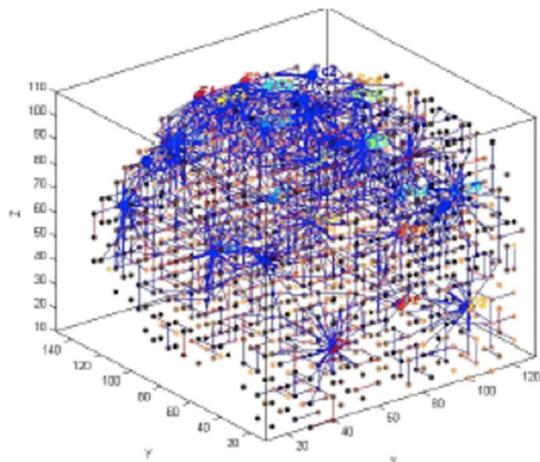
(a) Target stimuli
SNNc activation: 0.654



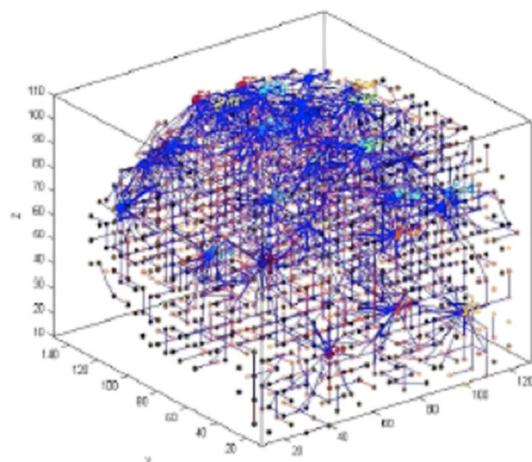
(b) Alcoholic feature
SNNc activation: 0.576



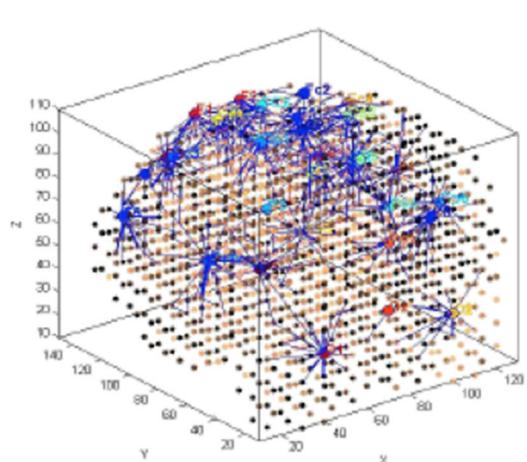
(c) Design feature
SNNc activation: 0.478



(d) Colour feature
SNNc activation: 0.512



(e) Non-alcoholic feature
SNNc activation: 0.426



(f) Brand name feature
SNNc activation: 0.301

◀ **Fig. 5** Mapping of the NeuCube-based SNNc according to the Talairach brain template [26] with distribution of 32 EEG channels as input neurons. Six SNNc have been defined and trained using the STDP learning with EEG data collected from nine participants when dealing with **a** target stimuli, **b** non-target alcoholic feature, **c** design pattern, **d** colour, **e** non-alcoholic, and **f** brand name features of drink products respectively. The average of the connection weights in each SNNc is also reported as an activation metric

plasticity (STDP) [29]. This learning process modifies the neuronal connection weights in relation to the time difference between post- and pre-synaptic firing. A connection weight is strengthened, if postsynaptic firing occurs after presynaptic firing; otherwise, it is decreased. Therefore, after the STDP learning is completed, the SNNc connectivity encodes “hidden” spatio-temporal interactions between the input variables. STDP learning rule is defined as follows:

$$F(\Delta t) = \begin{cases} A_+ \exp(\Delta t / \tau_+) & \text{if } \Delta t < 0 \\ -A_- \exp(-\Delta t / \tau_-) & \text{if } \Delta t \geq 0 \end{cases} \quad (1)$$

The $F(\Delta t)$ describes how a neuronal connection weight is modified with respect to the spike timing of the pre-synaptic and post-synaptic over the Δt time interval. When $\Delta t \approx 0$, the maximum values of the synaptic modification are defined by parameters A_+ and A_- . The τ_+ and τ_- parameters represent the interval between pre to post-synaptic spikes in which the synaptic increases and decreases respectively.

Supervised Learning and Classification with the Use of Evolving SNN Classifier

For classification/regression problem, the dynamic evolving SNN (deSNN) is employed [30] (other classifiers are also applicable [31]) for supervised learning. For every single training sample, an output neuron is created and connected to all the neurons in the trained SNNc. Then, the training samples are propagated once more over the SNNc for supervised learning. In this way, the spatio-temporal activation patterns of the trained SNNc, which have been modified by a specific sample, are now utilised to train an output neuron. The rank order (RO) [30] initialises the connection weight $W_{i,j}$ between neurons i and j (where i is from the trained SNNc and j is an output neuron) with respect to the *mod* variable (a modulation factor) and the order in which the first spike arrives to the j as described in the following:

$$W_{i,j}(t) = \sum \text{mod}^{\text{order}(i)} \quad (2)$$

At time t , the post-synaptic potential of j is computed as follow:

$$\text{PSP}(j, t) = \sum \text{mod}^{\text{order}(i)} W_{i,j} \quad (3)$$

Then, the connection weight $W_{i,j}$ will be further modified by a drift value to also consider the existence of next spikes entering to neuron j at time t in $S_j(t)$. After a neuron i sends the first spike to a neuron j , the next coming spikes to j will adjust the weight of $W_{i,j}$ by a small drift value as shown in the following:

$$W_{i,j}(t) = \begin{cases} W_{i,j}(t-1) + \text{drift} & S_j(t) = 1 \\ W_{i,j}(t-1) + \text{drift} & S_j(t) = 0 \end{cases} \quad (4)$$

The optimisation procedure was based on an exhaustive search algorithm which used an objective function to maximise the classification accuracy. The number of optimised parameters are encoding threshold; radius threshold in “small world connectivity” (SNNc initialisation); learning rate of STDP; the spiking neuron threshold; drift and mod; and deSNN classifier parameters. More explanation of the deSNN is presented in [30] and also in the guideline of NeuCube at www.kedri.aut.ac.nz/neucube/.

Results

This section includes our results driven by first the ERP waveform analysis and then the NeuCube-based SNN cubes.

ERP Components Analysis

In this section, grand-averaged ERP waveforms were extracted using EEGLab software [32]. As shown in Fig. 4, analysis of ERPs was restricted to Occipital, Parietal and Frontal channels: (O1, O2, P3, P4, F3 and F4). The higher peak amplitudes have been observed for N100 and P200 ERP components towards the target and not target (alcoholic and brand name) stimuli.

Figure 4 depicts that higher mean amplitudes of N100 in the occipital lobe and P200 in the parietal lobe are captured for target stimuli compared to non-target ones. However, a higher mean amplitude has been observed in the frontal regions for non-target stimuli (alcoholic feature) compared to target ones. The mean amplitude was measured slightly larger in the right hemisphere in the occipital and parietal lobes for target stimuli compared to non-target ones. The results show that when using traditional statistical analyses of ERP, it was not possible to differentiate the EEG patterns of target versus non-target stimuli.

To expand our understanding from underpinning patterns of the EEG data, we propose here an approach using the NeuCube SNN architecture to map the EEG data into a 3D SNN model and then train the model with dynamics of EEG data.

Mapping, Learning, Visualisation and Classification of EEG Data for Attentional Bias Recognition

Talairach atlas was used here for mapping EEG data into the 3D SNNc of 1471 neurons, each represents the centre

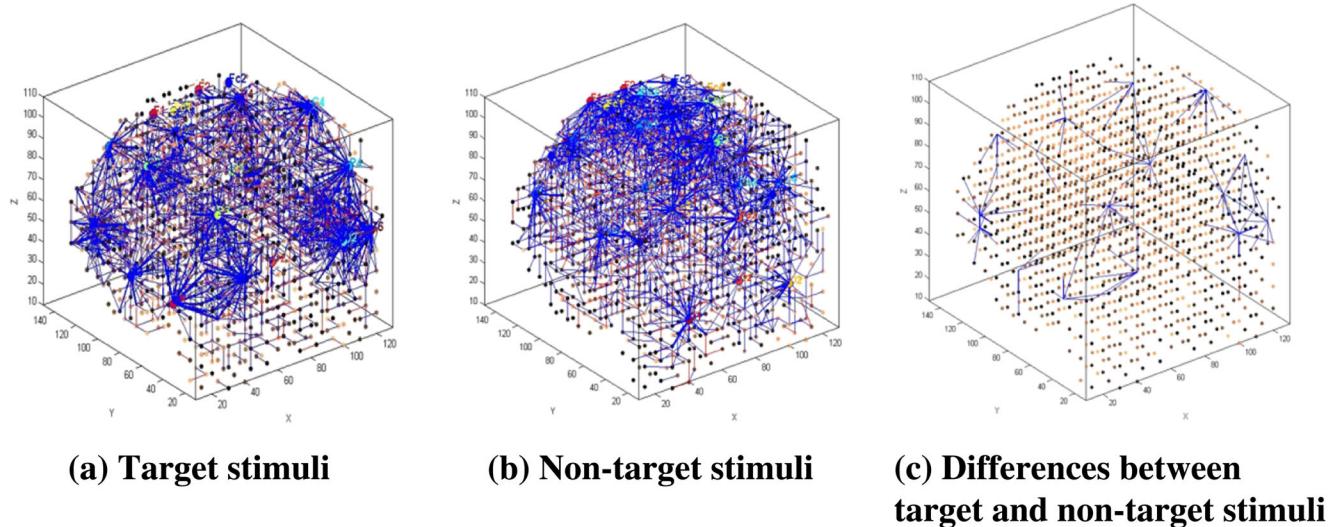


Fig. 6 **a** SNN connectivity trained on data of target stimuli. **b** SNN connectivity trained on data of non-target stimuli. **d** Two SNN models **a** and **b** were subtracted for better visualisation, interpretation and

understanding distinguishable patterns between two brain states. The connections in **c** depict the areas of the largest difference in brain activities

coordinate of 1 cm^3 area from Talairach [27, 28]. Then for every EEG channel, one input neuron was allocated in the SNNc with respect to the same (x, y, z) coordinate of the channel as positioned in Talairach (shown in Fig. 5). After the SNNc is spatially mapped, it was trained with spike trains using the STDP learning [29]. We trained six SNN cubes separately using different EEG data sample sets corresponding to target stimulus (which was a bottle of water), non-target stimuli (alcoholic/non-alcoholic feature, design, colour, and name of the brand).

Our finding in Fig. 5 represented the spatio-temporal connectivity corresponding to the consumer preference. In the NeuCube structure, the connection weights were learnt and stored in a long-term memory which can be later retained

and recalled. For a better interpretation of our result, we took an average of the positive connection weights in each trained SNNc and reported as an activation level for each product feature model.

We obtained the highest activation level of 0.654 in the trained SNNc that corresponds to the target feature (see Fig. 5). Figure 5a illustrates that strong connectivity was captured in an SNNc trained on EEG data associated with target stimuli. The connections were particularly enhanced between neurons located in the occipital lobe, corresponding to O1, O2 and Oz channels, which were less observed in the case of non-target stimuli in Fig. 5b–f.

During the cognitive task, the objective was concentration on the target stimulus, so the subjects became inattentive to

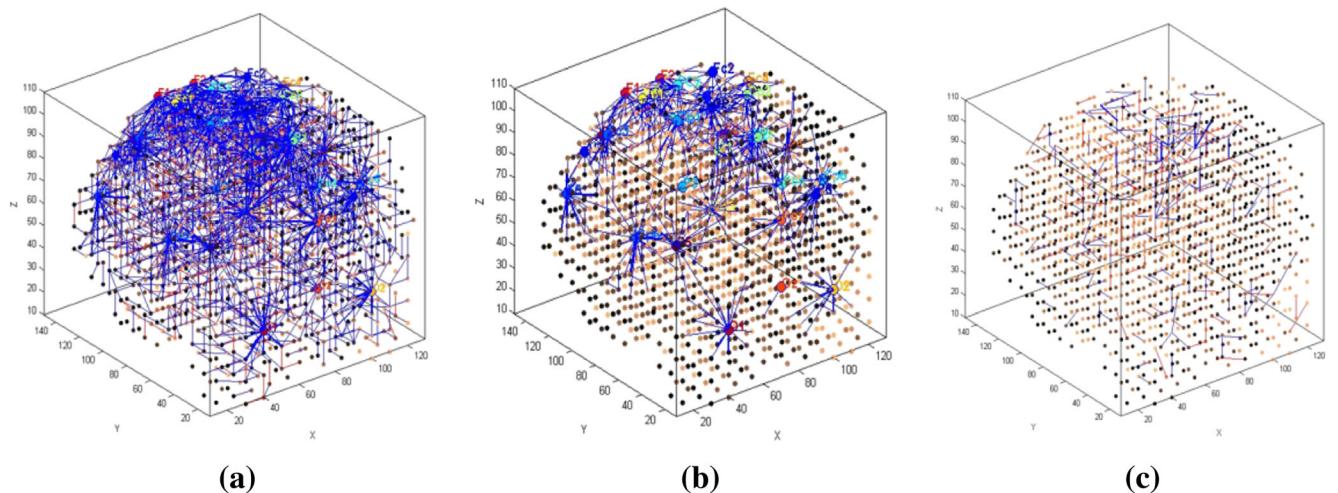


Fig. 7 **a** The SNN connectivity trained on data of alcoholic-related feature. **b** SNN connectivity trained on data of brand name related feature. **d** Subtraction of two created SNN models **a** and **b**, to visualise, and better

understanding of differences between two product features. The connection weights depict the brain areas where the largest difference in activity is

other stimuli set (the product features). Hence, irrespective of whether the subjects liked or disliked the drink features, we could study the attentional biases towards marketing products, captured as strong connections in particular areas of the SNNc as shown in Fig. 5b–f. The SNNc activation level values for non-target features were as follows: alcoholic feature 0.576, colour feature 0.512, design 0.478, non-alcoholic feature 0.426, and name of brand 0.301.

When we have identified remarkable activities in the SNNc trained on non-target stimuli, we aimed at discriminating these patterns and detecting the most dominant marketing feature among all. Our findings in Fig. 5f show that the brand name feature with the SNNc activation level of 0.301, has the least activation value than other drink features in Fig. 5b–e. The alcoholic feature was found more dominant over the other features as strong connections were captured in those EEG electrodes

positioned in the areas of parietal and frontal. The design and colour features of the product were less influential on the consumer attention as compared to the alcoholic feature.

The NeuCube findings revealed principally new information when compared with Fig. 4, by including both space and time components of STBD in the learning process. Using 3D visualisation of the SNNc allow for a better interpretation of the functional brain activity towards marketing stimuli. When observing an increased amplitude in Fig. 4 (resulted from EEGlab), a NeuCube model can reveal the corresponding brain regions which have contributed to this increase.

In order to investigate the differences between the SNNc trained on perceiving target stimuli versus the most dominant non-target ones (which was here the alcoholic feature), the two correspondingly trained SNNc were subtracted to expose the involvement of the brain areas towards attentional bias.

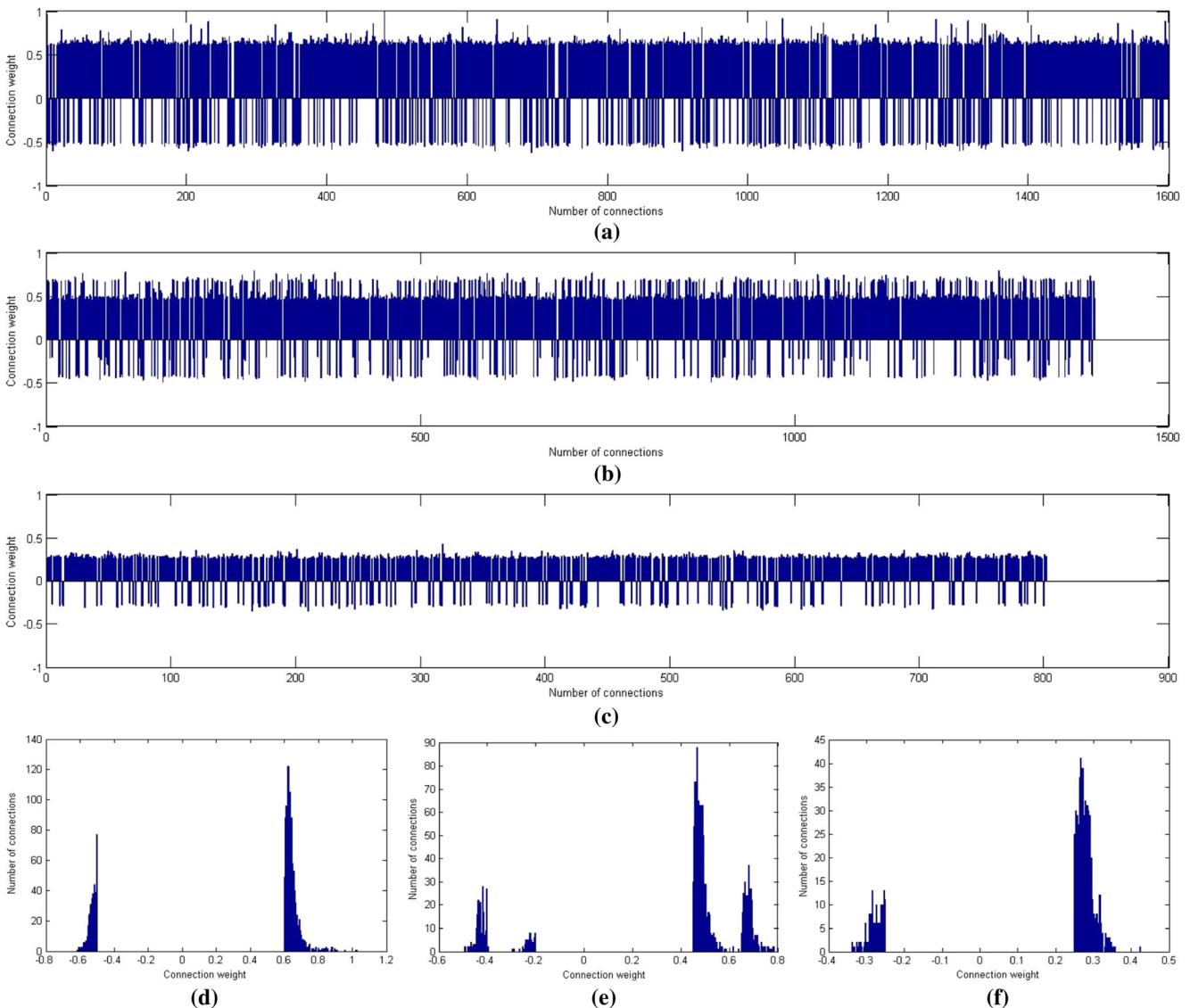


Fig. 8 The number of connections in the SNN trained of data corresponding to **a** a target stimulus, **b** alcoholic feature, and **c** brand name feature. The mean value of the positive connections are 0.6546, 0.5767 and 0.013 for **a–c** respectively as illustrated in **d–f** respectively

Figure 6a shows when the SNNc was trained on target stimuli, greater connections were enhanced around the EEG channels positioned in the Talairach areas associating with occipital and parietal compared to other areas. As shown in Fig. 6b for the non-target stimuli, strong connections were mostly created around the parietal and frontal regions. Figure 6c depicts that those neurons positioned around the EEG channel in the occipital lobes represented the most differences between target and non-target features. Similarly, we compared the brain states under perceiving two different non-target product features, “alcoholic feature-related model” versus “brand name-related model” as the most and the least influential non-target features in the SNNc connectivity respectively. Figure 7 shows that the most significant differences between the corresponding models have been observed around the PO3, CP5, CP6, P4, F4, F3 and F5 EEG channels, which are associated with executive functions in the brain.

Figure 7 confirms the literature that concluded attentional bias is involved in the executive functions as a set of cognitive processes [3]. As shown in Fig. 5, the spatio-temporal connections have been adapted differently in the five SNNc, reflecting different learning patterns of EEG data towards different marketing stimuli.

Figure 8 plots the connection strengths in the SNNc of target, alcoholic, and brand name features along with the histogram of the connection strengths.

In order to analyse the information interaction between the brain areas related to the tasks, we depicted the total temporal interactions between 32 input neurons (representing 32 EEG channels). In this graph, nodes are the input neurons and each

line that connects two nodes represents a number of spikes that are exchanged between them during the learning process. As illustrated in Fig. 9b, wider interaction lines were created between the 32 EEG data variables of alcoholic-related stimuli compared to the brand name-related stimuli in Fig. 9a. In the case of alcoholic-related stimuli, there were thicker interaction lines, especially between EEG channels positioned at the central-parietal and frontal areas (F3, F4, F5, F6, FZ, CP5 and CP6 channels). It reflects how attentional bias was driven in response to the alcoholic features. Our results prove that the SNNc visualisation is compatible with literature in neuroscience that stated perception of alcoholic-related content is processed differently from other product features by involving particular areas of the brain [6]. Containing the percentage of the alcohol-related cue on a drink product can make it more attractive and arouse the consumer attention.

Once the unsupervised STDP learning was finished, a supervised learning was employed to train the classifier. Our findings represent how the NeuCube architecture was able to distinguish the complex EEG samples related to different marketing features of a product.

EEG Pattern Classification in the NeuCube SNN Architecture

For the classification task, the EEG data samples were defined according to two classes related to the attentional bias towards target stimulus (class 1) and non-target stimuli (class 2). There were 90 EEG samples in total (45 samples per class).

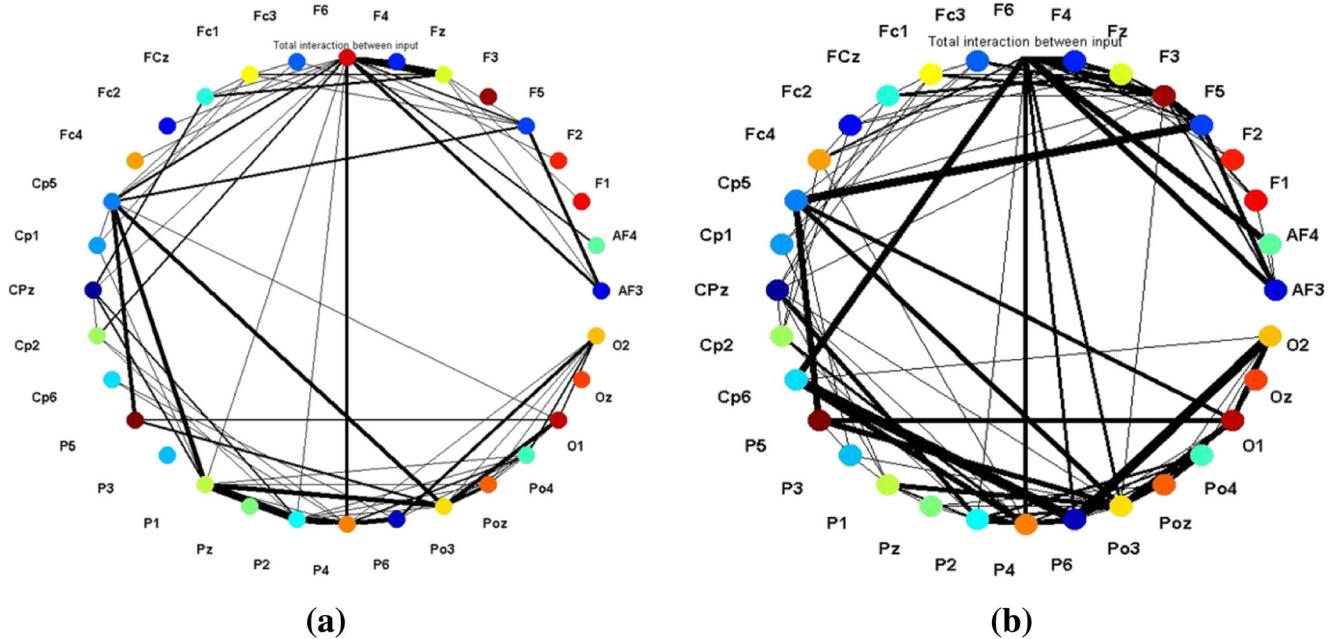


Fig. 9 Total interaction between 32 inputs in the SNNc during the STDP learning for **a** the brand name-related stimuli and **b** the alcoholic feature-related stimuli. Graph nodes represent the input neurons and lines

represent the amount of spike communications between the clusters of neurons that belong to the input neurons. Thicker lines represent more number of spikes are transferred between them

Table 1 A confusion table based on SNN methodology created through classification of data from 45 samples into two classes: Target stimuli (denoted as C1) and Non-target stimuli (denoted as C2). The

figures in the diagonal of the table in each class represent properly classified samples. Obtained classification accuracy is also compared with using traditional machine learning techniques

Confusion table obtained via the proposed NeuCube model			
EEG data Classes	Target stimuli (C1)	Non-target stimuli (C2)	Total accuracy %
Target stimuli (C1)	41	4	89.95
Non-target stimuli (C2)	5	40	
Obtained classification accuracy through traditional machine learning techniques with use of NeuCom			
Methods	MLP	MLR	SVM
Accuracy in %	49.50	48.50	48.50

For optimisation, we utilised a grid search of 1000 of iterations to maximise the classification accuracy and report the optimal values of NeuCube parameters. In this experiment, the main optimised parameters of the model are encoding threshold in $TBR = 0.19$; drift = 0.25 and mode = 0.4; radius of small world connectivity = 0.09; threshold for neuron spiking = 0.5 and unsupervised STDP learning rate = 0.02.

Table 1 summarises the classification accuracy achieved from NeuCube versus the conventional learning techniques. A confusion table is reported to show the miss classified samples vs the correctly classified ones when 50% of data (45 samples) was used as the training data and 50% for testing the model. The result represents greater classification accuracy with the use of NeuCube architecture compared to the traditional machine learning techniques.

As the most of the EEG samples have been classified accurately into the target and non-target classes, we intended to investigate how the EEG samples of the non-target class can be classified with respect to different marketing features as five classes (1 is alcoholic feature; 2 is non-alcoholic feature; 3 is design; 4 is colour, and 5 is the name of brand). Table 2 reports the classification accuracy obtained using the NeuCube for the five-class problem. There were 25 samples for training the model and 20 samples for testing it.

Table 2 A confusion table based on SNN methodology created through classification of EEG data from 20 samples into 5 classes: Alc (denoted as C1), Non-Alc (denoted as C2), design (denoted as C3), drink machine learning techniques

Confusion Table obtained via the proposed NeuCube model					
EEG data classes	Alc (C1)	Non-Alc (C2)	Design (C3)	Colour (C4)	Brand name (C5)
Alc (C1)	4	0	0	0	0
Non-Alc (C2)	0	4	0	0	0
Design (C3)	0	0	4	0	0
Drink colour (C4)	0	0	1	3	0
Brand name (C5)	0	0	1	0	3
Obtained classification accuracy via traditional machine learning techniques with use of NeuCom					
Techniques	MLP	MLR	SVM	NeuCube	
Accuracy (%)	17.78	15.56	13.33	90	

It is worth noticing that the designed cognitive task in this research was complicated as every presented image was an overlapping of many features with one prominent one (can be seen from Fig. 1). Because of coinciding of different features during the task, the EEG patterns have shown only slight variation in response to them. These minor differences could not be observed and classified sufficiently by means of conventional methods, including linear regression, multilayer perceptron (MLP), and Support Vector Machine (SVM). The reason is that these methods were developed mostly to apply to static vector-based data and are not suitable for modelling and learning from both temporal and spatial information in STBD as it is the case in the current paper and in numerous applications of STBD [17].

Visualising and Understanding of Individual Consumer Brain Activity under a Given Stimulus

NeuCube-based SNNs can be visualised in terms of connectivity and spike activity when recalled on data from each subject to understand what is the brain activity of this subject when presented with a given stimulus.

In order to study how subjects reacted to different non-target stimuli, we created a personalised SNNs using EEG data of four subjects (presented as four output neurons),

colour (denoted as C4), and brand name (denoted as C5). The figures in the diagonal of the table in each class represent properly classified samples. Obtained classification accuracy is also compared with using traditional

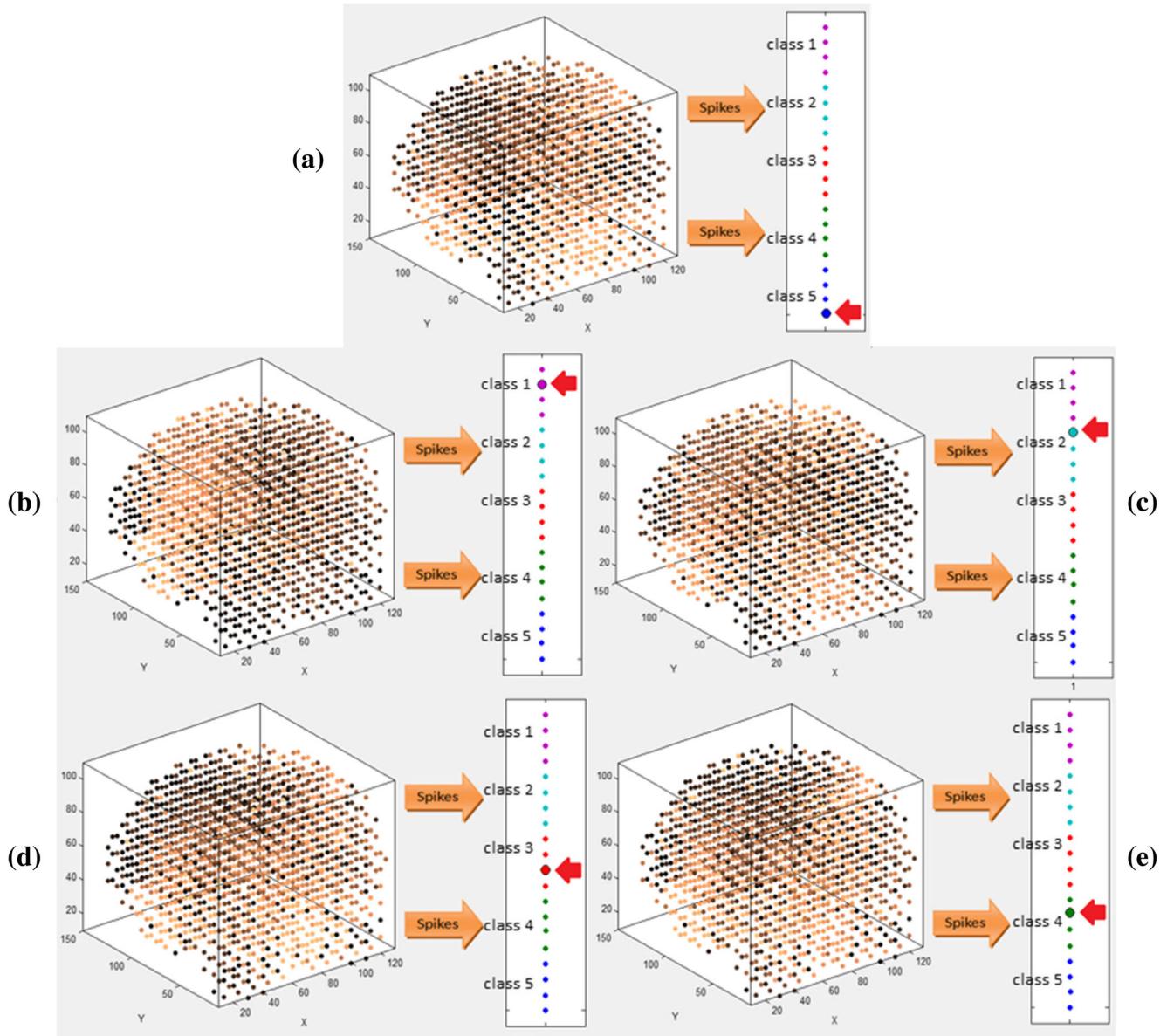


Fig. 10 Personalised SNN of randomly selected subjects, belonging to five classes (1: Alc; 2: Non-Alc; 3: Design; 4: colour, and 5: brand name). Each personalised SNN model is captured for one subject belongs to (a) brand name, (b) ALC, (c) Non-ALC, (d) design and (e) colour. For each

training sample, one output neuron is generated and connected to the neurons of the SNNc. The output neurons are labelled by their class information. Brighter areas represent larger connection between a neuron from SNNc to the output neuron

each presented with five stimuli. As explained in Section 3.3, deSNN was used as an output classifier (visualised in Fig. 10). For each sample, which represents the EEG data of an individual person under a given stimulus, one output neuron was created and assigned by its class information (purple: alcoholic; light green: non-alcoholic; red: design; dark green: colour; and blue: brand name). The connection weights between neurons in SNNc and neurons in the output layer were initialised using RO rule. The connection weights were further adapted with respect to the next spikes coming to the output neurons. After the STDP supervised learning procedure was

accomplished, the connection weights became fixed. This model is now visualised for individual subjects, each presented with a different stimulus. The connection weights for each of the five recalls are visualised by clusters of coloured neurons, which expose the importance of the area of the neurons in the SNNc to activate an output neuron. Brighter colour of neurons means a greater connection between a neuron in the trained SNNc and the output neuron. In the example in Fig. 10, Fig. 10a visualises the activity when the fourth subject was presented with stimulus 5. Figure 10b visualises the SNNc activity when the second subject was presented with stimulus 1.

Discussion and Conclusion

This paper represents that attentional bias in a marketing environment leads consumers to make a decision and choose a product. If we understand when and where attentional bias arises in the brain, we would be able to use the recognised patterns for the prediction of consumer decision. It can be used to develop novel, analytical tools for advancing marketing applications.

To address the research goals of this paper, we utilised specific neuroscience methods combined with the novel SNN computational architecture for a better understanding, pattern recognition and classification of STBD. We aimed at pattern recognition of attentional bias as an effective factor in consumer preference, which directs decision-making. For this purpose, we used a distraction paradigm task related to target and non-target stimuli. In the designed cognitive task, even though participants were requested to respond towards the target stimulus, our analytical results showed that their brain attentional biases have been driven by other non-target stimuli. As illustrated in Fig. 5, when subjects were dealing with target stimuli, stronger connectivity were evoked in the occipital regions of the trained SNNc in comparison with non-target stimuli. This finding indicates that the functional brain connectivity of the target stimuli can be mostly associated with visual attention. However, we did not detect significant connectivity in some parts of the brain areas related to the preference and decision-making towards target stimuli. The difference between perceiving the target versus the non-target stimuli was mostly formed around the O2 EEG channel as shown in Fig. 6c.

Our results indicate that in the field of neuromarketing, the name of a product may not significantly enthuse consumers by itself. However, attentional bias increases the consumer attention to a certain product, if the product brand name comes along with additional influential features (alcoholic or non-alcoholic, colour, etc.).

For comparative analysis of the non-target stimuli in Fig. 7, we found that attentional bias to alcoholic feature has led to affect EEG data more than other features. Greater connections were evolved in the frontal and pre-frontal regions of the SNNc in Fig. 7a compared to others in Fig. 7b.

Additionally, the NeuCube personalised SNN cubes identified the activated areas for an individual subject when presented with a certain given stimulus as shown in Fig. 10. We also performed a classification task on the EEG data case study using SNN cubes.

For EEG data analysis proposed in this paper, the designing of a NeuCube SNN model involved the below steps:

- Mapping the spatial information of EEG variables to SNNc;
- Unsupervised STDP learning phase in a spatially mapped SNNc [30];
- Visualisation and interpretation of the trained spatio-temporal connectivity in the SNNc;

- Supervised learning in the deSNN classifier [30];
- Parameter optimisation and validation of the model.

The experimental results obtained through the above steps have confirmed that our proposed method is promising and appropriate for pattern recognition of attentional bias in a marketing environment.

In comparison with conventional AI methods, the NeuCube has performed better in two phases: (1) the 3D brain-like structure of the SNN cubes and its capability of incorporating time and space components from STBD allow to study dynamic interaction between underpinning brain functions during a cognitive task (none of the traditional methods reported in Table 1 are proficient for such understanding); (2) significantly greater classification accuracy was obtained. Using the proposed model, we examined the patterns of neuronal activity during a complex cognitive task, such as measuring attentional bias towards marketing product features.

By using traditional methods such as EEGLab [32], we may differentiate the EEG patterns across different stimuli. However, the NeuCube learning and visualisation captures those areas of the brain that have made the contribution to this variation.

Two limitations of the study should be noted: (1) the sample size is rather small and number of subjects can be added to obtain precise analysis for future works and (2) genders can differ in response to a given stimulus. In this study, all subjects were male and we need to include females in the next stage of our research.

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Compliance with Ethical Standards The contents of this study are the authors' original work and the manuscript has not been published or submitted for publication elsewhere. Also we declare there was no disclosure of any financial support, conflict of interest to be made.

Ethical Approval The EEG data was collected from human participants. Prior to EEG data collection, ethical approval was granted by *Ethics Committee of Auckland University of Technology (AUTEC) New Zealand*, and informed consent was signed by every single subjects.

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