Variations in Neural Correlates of Human Decision Making – a Case of Book Recommender Systems

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Abstract

Human decision-making is a complex behavior. A replication of human decision making offers a potential to enhance the capacity of intelligent systems by providing additional user assistance in decision making. By reducing the effort and task complexity on behalf of the user, such replication would improve the overall user experience, and affect the degree of intelligence exhibited by the system. This paper explores individuals' decision-making processes when using recommender systems, and its related outcomes. In this study, human decision-making (HDM) refers to the selection of an item from a given set of options that are shown as recommendations to a user. The goal of our study was to identify IS constructs that contribute towards such decision-making, thereby contributing towards creating a mental model of HDM. This was achieved through recording Electroencephalographic (EEG) readings of subjects while they performed a decision-making activity. Readings from 16 righthanded healthy avid readers reflect that reward, theory of mind, risk, calculation, task intention, emotion, sense of touch, ambiguity and decision making are the primary constructs that users employ while deciding from a given set of recommendations in an online bookstore. In all 10 distinct brain areas were identified. These brain areas that lead to their respective constructs were found to be cingulate gyrus, precentral gyrus, inferior parietal lobule, posterior cingulate, medial frontal gyrus, anterior cingulate, postcentral gyrus, superior frontal gyrus, inferior frontal gyrus, and middle frontal gyrus (also referred to as dorsolateral prefrontal gyrus (DLPFC)). The identified constructs would help in developing a design theory for enhancing user assistance, especially in the context of recommender systems.

Keywords: decision support systems, human decision making, information systems, NeuroIS, recommender systems.

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1. Introduction

In decision making process, humans tend to rely heavily on advice provided by others [1]. Information Systems (IS) that support human decision making in online settings are referred to as Recommender Systems [2] [3]. In this day and age where users suffer from information overload problems, these systems help users explore and select available options. While decision making is generally perceived as effort-intensive and tedious [4], Recommender Systems may support the process by narrowing down choices, and that can be done in accordance with the inputs provided by the user. They are increasingly in demand because they enable intelligent human-machine interaction across a variety of fields. The performance of such systems depends upon their ability to correctly predict decision-making behaviour outcomes. Drawing upon the insights into how people choose and by understanding how users employ their cognitive, social, and emotional faculties during the decision-making process, the performance of such systems can be augmented. This augmentation derives from the designers focus on relevant dimensions extracted via HDM models.

Decision making is a mental activity that involves the activation of various faculties of the human brain. These faculties belong to different brain regions and include, but are not limited to, taking risks, evaluating rewards, or feeling pleasure. These various regions, known as neural correlates or "Brodmann Areas (BAs)" [5], are responsible in part for initiating a complex chain of neural processes when a human is making a decision. Neuroscientists have categorized these neural processes into cognitive, emotional, social, and decision-making processes. Recent literature in IS signifies a growing interest in these processes [6 – 8]. For example, in their seminal work, Taylor shows the effectiveness of modelling internal neurological activities to improve the design of Information Systems [9]. IS researchers increasingly use various theoretical constructs to understand the manifestation of these neural processes in human behaviour. In fact, most of the brain processes can be identified with a distinct IS theoretical construct [10] The focus has been on identifying macro human behaviours that roughly correspond to these processes to understand better how the human brain functions? and then how to best utilize that information to provide actionable insights on improving recommender systems.

Against this background, this paper documents a study exploring the role of various well-established theoretical constructs in human decision making. By looking at the origin of the brain signals, this study sought to explore how individual neural correlates impact the way human opt from a variety of objects. While doing so, the study used the context of an online book recommender system. In addition, another aim of this study was to establish the soundness of the experimental procedures when conducting a standard NeuroIS study. As an emerging sub-field of Information Systems, NeuroIS makes an extensive use of brain-imaging tools and techniques. Traditional IS research has employed qualitative and mixed-method instruments (e.g., surveys and interviews) for data collection. However, a major limitation of using these data collection approaches is that they tend to suffer from self-reporting bias. An increasingly common methodological approach in IS research is using neurophysiological tools, for instance, fMRI and Electroencephalography (EEG) [see 11–14]. Instead of relying on self-reported data, these tools offer the potential to directly capture users' brain activity. Taking into consideration the fact that such methods are less prone to self-reporting bias as well as not narrowly numerical in nature, this study makes use of neuroimaging data to address the research questions.

Electroencephalography (or EEG) has emerged as a powerful tool that senses electrical signals in the brain when different regions of the brain get activated during a mental activity [11] [15]

This study used EEG to record electrical brain signals. The collected data were further processed to obtain source localization. Once the source was localized, a particular IS construct was mapped onto this brain source, indicating the involvement of the construct in the specific decision-making process. The use of EEG to understand neurophysiological variations in decision making offers the potential to uncover what happens in the brain during a rather complex, choice-making activity after a recommendation has been made.
This study's key contribution is a systematic understanding of how people make decisions by giving clear insights into the cognitive and affective foundations of decision-making, which is evidently influenced by information system recommendations. The discovery of such foundations will provide a methodological contribution to the larger discussion concerning how Human Decision Making (HDM) occurs in recommender systems (RSs). As a result, it may be possible to create RS that are easier to use and make suggestions that are more accurate. This paper presents an experience of conducting a NeuroIS study. The results accumulated therein offer a useful and replicable baseline for similar NeuroIS studies and complementary behavioural studies used to gain insights into the human decision-making process after an interaction with a Recommender System. As mentioned earlier, this NeuroIS study used the context of book recommender systems and aims to explore the role of certain IS constructs thereby addressing the research questions like *what are the (probabilistic) individual neural correlates of HDM in content-based book recommender systems*, and *which (probabilistic) constructs (dimensions) of HDM get activated when a decision-making activity is performed in content-based book RSs?*

2. Related Work

In the field of IS, neural studies are considered interdisciplinary as they combine different areas of research such as cognitive neuroscience, human decision making and information systems. This section briefly discusses human decision-making in recommender systems intending to contribute to the NeuroIS domain.

2.1. Human Decision Making in Recommender Systems

Human decision making is a complex process a human brain has to go through before reaching a final choice. The field has been researched from various perspectives, for example, psychological, cognitive, and normative. Initial research into the combined domain of decision making and recommender systems highlighted the richness and complexity of various decision points, specifics of group decision making, and modelling the impact of contextual factors in a variety of decision making processes supported by the recommender systems [16]. In their seminal work, Chen's article recommended examining personal factors potentially influencing a user's ultimate choices, for example, current mood, personality type, and emotions. These factors in fact can be used to develop a preference construction and/or choice making model. While several studies have explored the preference construction model, most of these studies drew insights from self-reported data and, therefore, may suffer from self-reporting bias. Jannach et al. presented a research landscape from the recommender systems domain [17] and highlighted the need to find innovative approaches to better understand choosing behaviours. They revealed how user's choices in a recommender system may be linked with the specific situation and goal of the user. Therefore, how users with different goals perform selections under different situations merits more research.
Gonzalez and colleagues further explored the constructs of decision makers' mood and emotion recommender systems [18]. In the same year, Xiao and Benbasat [2] explored the

social IS construct of trust in recommender agents and, made a unique theoretical contribution to the Technology Acceptance Model (TAM) [19]. Also driven by the TAM, Hu and Pu explained the role of personality in decision making in recommender systems [20] Their findings had implications in the design science domain. Similarly, Chen et al. [16] also described the critical role of personality behaviour in human decision making within a recommender system. On the other hand, Xu et al. [21] discussed a trade-off between transparency and product diagnosticity on the basis of the Effort Accuracy Framework. Among other work in this field, Gerhard Leitner also benefitted from TAM to discuss various human decision making types and respective psychological theories in the context of financial recommender systems [22].

A great deal of previous research has focused only on exploring certain features of human decision making, and no systematic model for human decision making in recommender systems has ever been proposed. A recent study [23] has explored the fairness and accuracy of RS through existing datasets like ML-100K, ML-1M (Movie domain) and BookCrossing (Book domain) . But they address the impact of data characteristics from these datasets in a systematic way only. Another group of researchers [24] studied a Pakistani diabetic patients database (Medicine domain) by applying regression models on the data characteristics. Hence, the human decision-making factor is not taken into account. Moreover, a detailed discussion on the relative importance of large number of decision factors is still missing from the literature, which is critical since each one of them explored the decision factors but rather distinctively. In this paper we attempt to look at the factors collectively and pave way to explore their relative weightage in future.

2.2. Neuroscience Information Systems (NeuroIS)

Contemporary IS researchers have been interested in identifying the exact brain areas/features that are activated when a user makes a choice or a decision in a recommender system [25], [26] Recent work explores the role of neural correlates of decision making in information security [27] and neural correlates of multidimensional visualizations [28] where the earlier performed an ERP (Event Related Potential) analysis and the latter conducted an fMRI comparison of graphs using evolutionary theory. However, little attention is paid to addressing this in the context of recommender systems [16] Popular IS theories like the theory of reasoned action, prospect theory, TAM, Social Agency theory and effort accuracy framework have been used for the said purpose [17] Some established NeuroIS tools include fMRI, EKG, and EEG. These tools can also be used with traditional IS tools like questionnaires, surveys, and structured interviews. Also, triangulation of measures may provide an improved validation across the measures, eventually leading to an enhanced ecological validity of IS studies [11] Recent works have also evaluated the perspective of anthropomorphism and interaction with anthropomorphic recommender systems [29] and provided useful insights. This would help improve the design science of intelligent systems, in general, and recommender systems, in particular.

2.3. Cognitive Neuroscience and Information Systems Constructs

According to the previous literature, there are four major categories of brain processes; decision making processes, cognitive processes, emotional processes and social processes [14]. In the context of recommender systems, human decision making uses a combination of these processes. The phenomenon indeed is complex in nature. In fact, any activity performed by a human has its action's signals originating from diverse areas of the brain and are not generally restricted to one area. That means there is no one-to-one relationship between a brain area and a task, activity, or process.

A comprehensive selection of constructs that maps the decision-making behavior can be deduced from multiple sources. These constructs are primarily the contexts that influence the users' decision making. The list includes but is not limited to the following: rewards, uncertainty, ambiguity, risk, motor intentions and calculation constructs from the decision-making processes, "theory of mind" construct from social processes, pleasure and emotional processing construct from emotional processes, and cognitive effort construct from cognitive processes.

It is important to note here that the activity of choice decision in recommender systems is arguably both social and calculative. Therefore, based on the proposition by [30], the brain areas associated with the "theory of mind" are considered. It was found that the anterior paracingulate cortex gets activated when individuals express their beliefs about the social reasoning of others. Similarly, the medial prefrontal cortex is stimulated when making decisions and choices based on calculative expectations of what others will do. Using the insights from Quazilbash et al. [8], the calculation IS construct also shows the same prefrontal cortex and anterior cingulate cortex as associated brain areas. Previous research also shows that consumers' first choice decision is usually more social than rational in nature [31], i.e., higher activation in the ventromedial prefrontal cortex and lower brain activity in the dorsolateral prefrontal cortex. Based on the above discussion, it can be deduced that the frontal lobe plays a vital yet complex role in human decision making within a recommender system. It describes decision making in terms of rewards, uncertainty, and the theory of mind, i.e., calculative cognition and social considerations. In addition, based on social adaptive learning, we know that "following advice may be intrinsically rewarding" i.e., the brain process and/or the IS construct that is involved in following the advice is a reward [32].

Overall, these results indicate two outcomes that helped us design this study. First, that choice decision making within a recommender system is a kind of social learning activity. Second, the reward construct may be closely associated with choice decision making while seeking advice [8]. It is worth mentioning here that the brain areas associated with the rewards construct are the orbitofrontal cortex, medial prefrontal cortex, and amygdala. This has been discussed further in the following sections. EEG signals have a low spatial resolution; therefore, it is assumably safer and more appropriate to mark the prefrontal cortex as the specified brain area along with the amygdala.

Regarding online recommender systems, online transactions are considered inherently uncertain in nature [33], and often people do not feel completely sure while selecting something online. That means the brain process and/or the IS construct behind transacting online may be of uncertainty. The brain areas associated with uncertainty are the orbitofrontal and parietal cortex[14], [34], [35] Therefore, orbitofrontal and parietal cortices might show higher brain activations during a human decision-making activity.

Moreover, in previous work, ambiguity has been presented as a cognitive bias in decision making where people tend to choose an option about which they have some prior information instead of selecting an option which might be the best choice in reality. However, the researchers have limited knowledge about it (for more detail, see [36]). The brain areas associated with this type of activity were found to be dorsolateral prefrontal, anterior cingulate, parietal, and insular cortex [35] Previously, Dimoka et al. [14] have outlined ambiguity as an IS construct and highlighted the parietal and insular cortex as primary areas of brain activity during a human decision-making process. As discussed earlier, the construct of trust has already attracted widespread attention from NeuroIS researchers. Still, lesser importance has been laid on investigating the dynamics of distrust. Several studies identified trust as an important construct [37]–[39], but others (for e.g. [33]) were found to be focused more on distrust. However, as suggested by [40], more research and further in-depth exploration need to be undertaken on this topic

2.4. Existing solutions from system and network perspectives:

Many domains are implementing and/or designing solutions using the interdisciplinary approach. Solutions are witnessed in an effort towards decision support systems in disparate sectors. Few examples are discussed below.

Studies in Internet of Things (IoT) are receiving substantial attention. Creation of DSS and implementing HDM models is becoming more prevalent in the research community nowadays and people are exploring the role of DSS by creating HDM models. One such survey [41] conducted by Li and colleagues shows a significant growth in number of publications (in DSS models for energy management approaches , including IoT domain) from 2015-2020. IoT's participation knows no boundaries these days and its applications can be witnessed in healthcare systems as well [for details see [42], [43]].

3. Methodology

3.1. Experimental Design

Experiments were designed to gauge the brain patterns of human subjects. An Electroencephalography (EEG) device was used to capture evoked brain signals in response to recommendations shown to a user. The signals were captured multiple times and then averaged. This technique helps in averaging out the background brain activity and elicits the signal specific to the stimulus. Use of EEG bio-signals in order to study information systems dynamics, is becoming increasingly popular nowadays (see, for example [44], [45])

Source localization was performed with the help of these elicited signals. The source localization was performed for signals acquired from each of the subject in the sample. This process helps identify the location of activity in the brain that was incited by the stimulus. Source localization is an inverse problem[1] in EEG [48], and to date, there is no unique solution for this problem.

In terms of sample demographics, the experiment was guided by a well-cited book recommendation dataset; Book-Crossing [49]. Right-handed healthy individuals with correct or corrected eye vision aged between 18 to 45 years were recruited. These human subjects had to undergo a rigorous training process before taking part in actual readings. The overall exercise aimed to reduce anxiety and discomfort that may occur while interacting with the EEG apparatus and ensure enhanced technology acceptance.

For statistical analysis, the EEG files were analyzed using sLoreta software. The software employs sLoreta algorithm to perform the pre-processing (e.g. averaging) and localize the strongest source [50]. Amongst other limited approaches used to address the inverse problem of source localization in EEG, Loreta has been widely recognized to provide the best results [48], [51] For example, if two or more sources are of interest, then Loreta with p equals to 1.5 performs better. But, if only one strongest source is of interest, then sLoreta gives best result. However, all algorithms (sLoreta, MNLS and Loreta) have more difficulty reconstructing a

[1] Inverse problem is referred to as the problem of reconstructing the source from the given/ measured signals. It is ill-posed in nature meaning that the problem that does not meet the "Hadamard Criteria" for well-posed problems. The criteria is as follows: 1) has a solution, 2) has a unique solution and 3) has a solution depending continuously on the input parameters. [46], [47]

source when its relative strength is reduced. [50]
This research aims to uncover a combination of brain areas that probabilistically participate most actively in the human decision making in recommender systems in correspondence with their respective IS constructs. The results are shared by mapping constructs from the four categories of brain processes (i.e., cognitive, social, emotional, and decision-making).

3.2. Materials and Participants

To decide the sample of participants, this study used a book recommendation system data as the test system. Within the book recommendation system data (BookCrossing dataset [49]), a total of 278860 users who received recommendations, only 36% of the users shared their age. Age group ranging from 18-45 were found to be the most active group of users. Against this background, this study also recruited participants from the same age group. 16 students and young faculty members of a business school at a large university were recruited. The student participants were given a credit-based incentive as a subject recruitment drive. After filling out a consent form and subject information sheet, the participating subjects volunteered to participate. It was made sure that recruited right-handed healthy individuals had good eyesight and no reported injury to any part of the brain.
The sample size was determined using the G-Power tool, as shown in **Fig. 1**. In terms of gender distribution, there were slightly more females (n = 10) than male subjects (n = 6). All subjects were first trained in a lab-based setting. The main experiment was then conducted in the same environment. A neutralizer (also known as fixation cross) screen was shown to the participants for 15 seconds, followed by a screen showing a set of book recommendations. The participants were briefed about the study beforehand and, therefore, were trained enough to generate focused Beta2(20-30 Hz) level outputs.

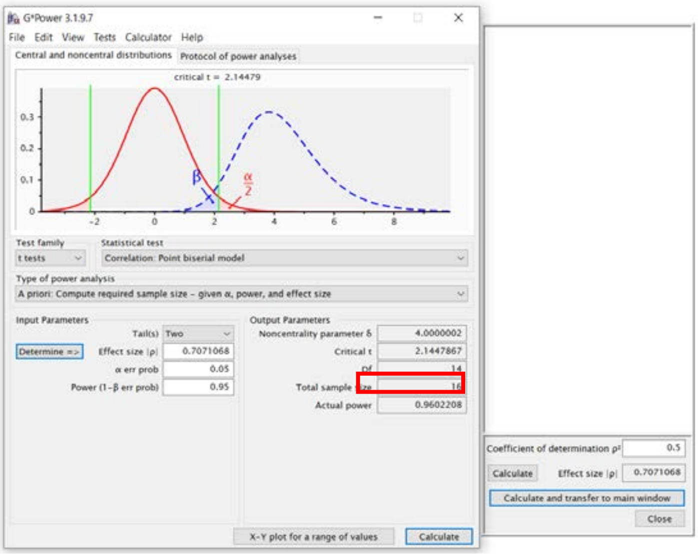


Fig. 1. G-Power calculates a Sample Size of 16.

3.3. Data Collection

This study used EEG as the primary neurophysiological data collection tool. The specifications of the device are as follows.
EEG -Montage of electrodes: MDX NeuroPro32 device was used, which works with wired dry electrodes and has a sampling rate of 200 Hz. Nineteen electrodes were mounted on subject's scalp with the help of a rubber mesh cap. The cap's position was measured by the international 10-20 system.

3.4. Experimental Instructions

Each participant was tested individually for the study. Each participant was briefed about the experiment and the study beforehand. The brief was shared verbally and via a handout. The EEG electrodes were placed on the subject's scalp. In order to avoid any discomfort due to gel usage, dry electrodes were used throughout the experiment.

3.5. Experimental Procedure and Measurement

A random list of books was shown to the users in an online bookstore. The users were tasked to "*Select a book that they would purchase from an online bookstore, and then make another selection from a set of given recommendations*". The recommendations were based on the book the subject selected in the first place. The EEG signals were recorded starting from the time the recommendations were shown as visual stimulus up till the time the user made a final choice from the recommended options. The same procedure was repeated for all subjects. The subjects were thanked, debriefed, and dismissed upon the completion of the experiment. The average total time under EEG scanning was estimated to be 15 seconds.
In line with the recommendations from previous work [15], the signals were captured 16 times and then averaged. This technique helped in averaging out the background brain activity and eliciting the signals specific to the stimulus. Source localization can easily be performed with the help of such elicited signals. IS construct-to-brain area mapping (i.e., localization of correlates) was carried out using the same software. First, the .edf files from EEG software were converted into .txt files. Then Event Related Potential (ERP) analysis was performed on these text files. Results are discussed in the next section.

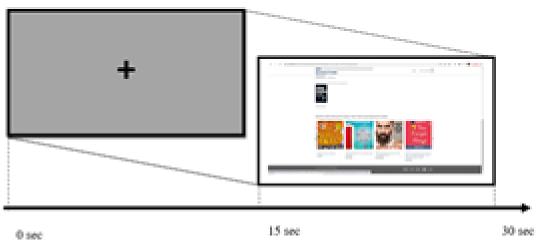


Fig. 2. Graphical Representation of EEG Experimental Procedure

4. Results and Discussion

A close analysis of the readings suggested that subject 2 and subject 6 produced similar output, i.e., Precentral gyrus. Since the participants were not supposed to click their choice via mouse (to avoid any motion signal incorporated as noise) and were only required to make a mental selection therefore they were explicitly asked after each reading if they have made a choice yet or not. Their response was an affirmative every time.

The results are shown in **Table 1**. The final fMRI like outputs created by sLoreta tool are shown in **Table 2**. The colour scales were defined disparately for each sLoreta outcome. An example of Posterior Cingulate in Subject 16 is as shown in **Fig. 2**.

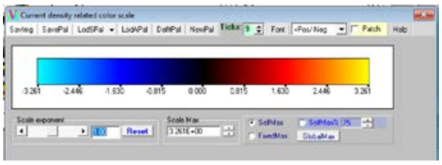
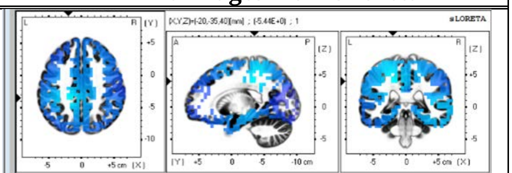
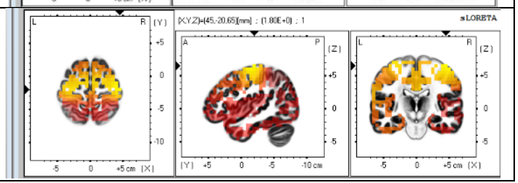


Fig. 3. Color Scale for Posterior Cingulate in Subject 16

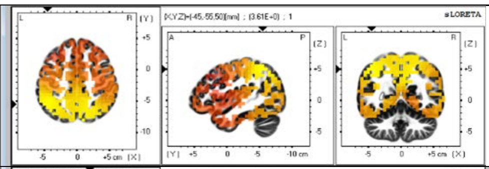
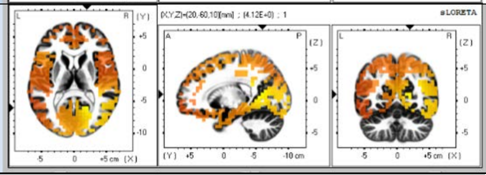
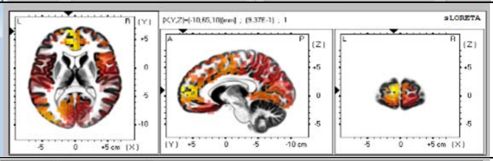
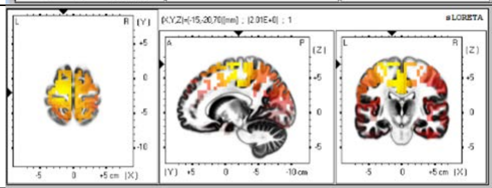
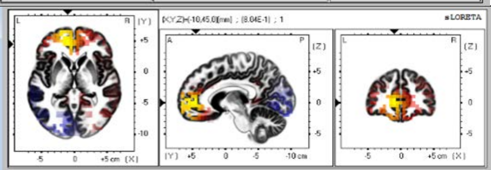
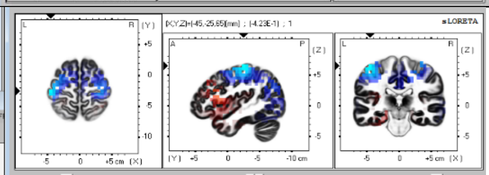
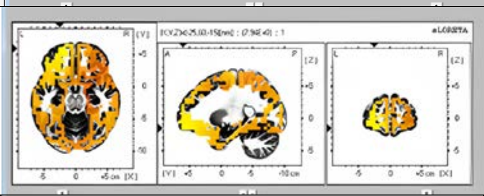
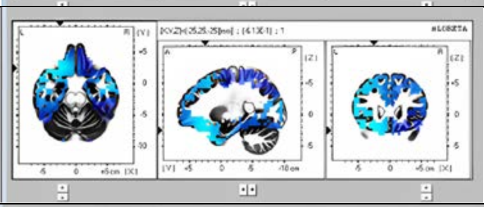
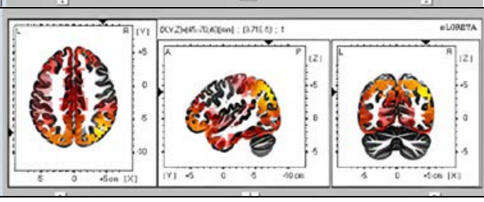
Table 1. Brain Area – IS Construct Mapping

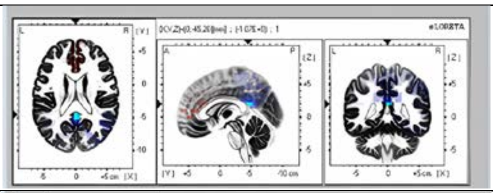
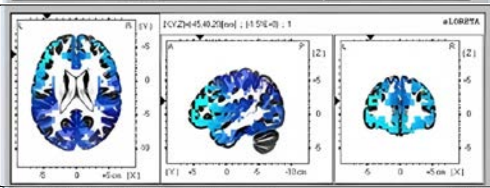
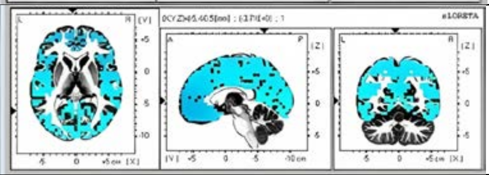
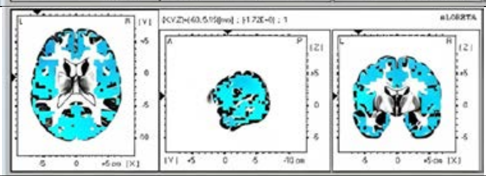
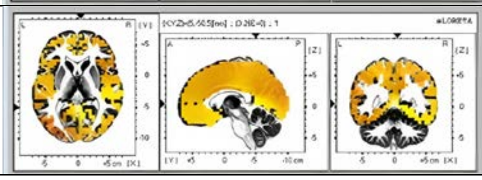
Subjects	Brain Area	Brodmann Area (BA)	IS Construct
S1	Cingulate Gyrus	31	Reward, Theory of Mind[52]
S2	Precentral Gyrus	4	Risk[53]
S3	Inferior Parietal Lobule	39	Risk[53]
S4	Posterior Cingulate	30	Emotion[54]
S5	Medial Frontal Gyrus	10	Task Intentions[40], [55]
S6	Precentral Gyrus	6	Risk[53]
S7	Anterior Cingulate	32	Ambiguity, Calculation[56], [57]
S8	Postcentral Gyrus	3	Sense of touch[58][2]
S9	Superior Frontal Gyrus	11	Reward, Decision Making[59]
S10	Inferior Frontal Gyrus	47	Theory of mind[60]
S11	Inferior Parietal Lobule	39	Risk[53]
S12	Posterior Cingulate	30	Emotion[54]
S13	Middle Frontal Gyrus (also referred to as DLPFC)	46	Emotion[54]
S14	Posterior Cingulate	30	Emotion[54]
S15	Precentral Gyrus	4	Risk[53]
S16	Posterior Cingulate	29	Emotion[54]

Table 2. MRI-like images from sLoreta

Subject No.	Brain Area	MRI-like images from sLoreta
1	Cingulate Gyrus	
2	Precentral Gyrus	

[2] The brain area namely Postcentral Gyrus has so far not been explored by NeuroIS researchers in lieu of IS constructs. However, in cognitive neuroscience it pertains to the sense of touch that is generation of a brain signal against someone touching the subject's hair(s).

3	Inferior Parietal Lobule	
4	Posterior Cingulate	
5	Medial Frontal Gyrus	
6	Precentral Gyrus	
7	Anterior Cingulate	
8	Postcentral Gyrus	
9	Superior Frontal Gyrus	
10	Inferior Frontal Gyrus	
11	Inferior Parietal Lobule	

12	Posterior Cingulate	
13	Middle Frontal Gyrus (also referred to as DLPFC)	
14	Posterior Cingulate	
15	Precentral Gyrus	
16	Posterior Cingulate	

There are several key findings from this research. Firstly, it identifies the neural correlates of decision making in recommender systems showing that reward, risk, theory of mind, emotion and task intentions are closely associated with the selection decision of an object (e.g., a book) from a given set of recommendations. Secondly, it shows that there does not exist a one-to-one mapping between processes and IS constructs as the findings identified disparate brain areas during multiple iterations of the same decision-making activity. Thirdly, it reflects that the activity of decision making is not solely cognitive in nature but is combinatorically cognitive, emotional, and social in nature. This can be seen in **Table 1** that risk, and reward are pure decision-making processes whereas emotions belong to emotional processes and theory of mind is a social processes' construct [10]. Fourthly, the results and experience from this study proved that the methodology adopted for addressing the problem is not only well suited and produce appropriate results but also paves way for the future studies to be conducted with confidence. Finally, the results reflect that while deciding about selecting an option (e.g., a book) in a recommender system setting, the users generally make use of more than one of their cognitive abilities. However, some cognitive abilities were observed multiple times, as shown in **Table 1**.

Overall, it was observed that although multiple cognitive constructs were employed simultaneously, there was usually one construct that was highlighted more than the others. The researchers arrived at this observation by studying the outputs of sLoreta, which consistently showed the occurrence of some constructs repeatedly. However, some constructs uniquely observed as well. When multiple brain areas function at the same time while performing an activity, sLoreta identified the strongest source from them. This finding was in line with [50]. The results from **Table 2** are representative of that for each iteration and reflect that reward, theory of mind, risk, and emotion were majorly playing a role in human decision making in recommender systems. One potential reason for this could be that humans generally deal with several emotions at the same time during any activity.

5. Implications for Theory and Practice

According to the study's findings, reward, theory of mind, emotion, task intention, and ambiguity are among the processes that influence recommender system decision-making, with risk and calculation providing further cognitive support. The findings imply that one of the neurological basis of HDM in recommender systems is reward. This indicates that when users choose a recommendation from a list of suggestions made to them, they find it valuable enough to view it as a reward. The finding aligns with previous literature where "following advice" was termed an intrinsically rewarding behaviour [32]. The user may think so since it eliminates the burden of exerting additional effort to search for an item from scratch (e.g., a book to read in this case). It facilitates decision-making by offering ideas that would also cut down on time spent looking for alternatives. In short, recommender systems may encourage minimising the extra effort brought on by cognitive load [61].

At the same time, when a user is following the suggestion provided by the system, they also tend to think about how these suggestions would have come up in the first place. Technically speaking, the user is in fact, thinking about the algorithm running behind the recommender system either intentionally or unintentionally. This curiosity surfaces more naturally and strongly in some users than others but is never non-existent. Previous literature has often referred to this phenomenon as the construct of "Theory of Mind" [10]. Thinking about a more social approach to how others might have come up with a similar choice, this construct is also associated with the very cognitive "calculation" construct within itself. Therefore, we find calculative cognition and social considerations wrapped up in one activity of decision making. As outlined in section 2.3, the brain areas responsible for these activities are the prefrontal and anterior cingulate cortex, the latter being the primary one. However, in this study, it was observed that the brain area 'cingulate gyrus' has been playing a major role here and not specifically anterior cingulate cortex. Since the cortical region in a human brain lies beneath the gyrus for which there is limited spatial resolution, as a result one can safely associate cingulate gyrus with theory of mind. The risk here clearly takes the leading position while the theory of mind follows (calculation being an integral part of theory of mind is counted within).

A distinct practical implication lies here from the design perspective. Suppose we know users' decision-making model on a recommendation interface, we can infer how the user will select from the given recommendations. That means what kind of factors are they going to employ while making a choice from a set of recommendations shared with them. For instance, in this case, if the results show that the users find a book from the recommended items riskier, then the recommendation algorithms can be improved by mitigating risk factors on users' behalf. This, in turn, has theoretical implications on effort-accuracy trade-off in a way that reduces risk (per se) and possibly leads to an overall reduced effort in decision making. The results (as shown in **Table 1**) also show that the users were not only thinking with a reward-based approach while making the decision but also calculating in terms of comparison of prices of books and associating some emotional value with it while intending to take the decision.

Moreover, the user also may have considered how the system is generating these recommendations. Hence the recommendation algorithms can be improved taking these factors into account as in mitigating effort intensive calculation and providing explanations to satisfy the theory of mind construct. This conforms to the directions provided by [62] in which the researchers recommended using side information to describe the internal mechanisms, consequently leading to the use of black-box-like algorithms. This helps in not only improving the design of recommender systems but also in understanding the black box of human brain in terms of decision making.

Another important construct that could have been playing a role is ambiguity. Occasionally, the users were slightly unsure while deciding which recommended book to finally go for. This behaviour implies that since being ambiguous may lead to either poor decisions or more time spent on deciding therefore designing recommendation algorithms in a way that aid in reducing the ambiguity may result in better overall perceived user experience as well as better effort-accuracy trade-off. This can be achieved either by adding more points of comparison or highlighting unique features, or both.

All in all, no traces of uncertainty and motor intention were found in the results though there is a caveat attached as uncertainty may surface in future readings. But it seems unlikely for motor intention, as the statistical analysis used in this research filters out noise (i.e., the brain signals) that may be generated by motor signals. Also, since the users were not asked to click on the selected option and instead make a decision mentally, this approach might have been restrictive for the motor signals, preventing them to get activated, which under normal circumstances are assumed to take part in a similar activity. A consideration of motor skills in human decision making in recommender systems, therefore, merits more research.

Hence a direct practical implication lies in the fact that if we can incorporate these constructs in RS design, then it will have a significant impact on designing better RS. However, on a theoretical implication front, it will help us in understanding the human decision making in a more refined fashion.

6. Limitations and Future Directions

There happens to be certain technical limitations for this research as we have access to a particular type of EEG apparatus (as described earlier). Such technical limitations are a norm in the experiments conducted in lab settings.

This research is being conducted in an environment which is socially and culturally different from NeuroIS studies that have been done before. The experiments in this study were conducted in a developing country and hence if conducted in a developed region may tend to produce similar or different outcomes. This not only depicts the challenges one might have to face due to limited resources and lack of awareness amongst subjects regarding such studies but also calls for future research in this context.

The overall experience from the study provides a strong case to take into consideration other contexts, as a replication performed in a different context (e.g., ethnicity, education level or prior experience with decision making in a digital environment) may yield even more interesting results in future.

Additionally, NeuroIS researchers can examine the "post central gyrus" brain area to study its role as an IS construct in information systems (generally) and decision support systems (especially).

In all 10 distinct brain areas were identified. These brain areas that lead to their respective constructs were found to be cingulate gyrus, precentral gyrus, inferior parietal lobule, posterior cingulate, medial frontal gyrus, anterior cingulate, postcentral gyrus, superior frontal gyrus, inferior frontal gyrus, and middle frontal gyrus (also referred to as dorsolateral prefrontal gyrus

(DLPFC)). In the next step we plan to employ eLoreta to figure the relative weightage of each of the identified constructs.

7. Conclusion

This experimental study was aimed at identifying the neural correlates of HDM. The analysis suggests that HDM is neither a unidimensional activity nor involves multiple cognitive abilities to generate what appears to be a simple act of deciding which book to read from a given list of books online. Adding to the assortment are constructs like emotion and task intention that surface naturally. As impassive as a simple act of picking a book to read might appear, it can be highly emotional as well as deeply cognitive. Therefore, the experiment was set up to uncover the combination of brain areas that are relatively more participative in the HDM in RSs in correspondence with their respective IS constructs.

The study provided preliminary insights into the very activity of human decision making in an online book recommendation system setting, thereby proving the soundness of the methodology. While providing valuable and actionable insights about how the decision making takes place, this work offers the potential to be used as a template for conducting EEG based NeuroIS studies by discussing the methodological details at a stretch. Although EEG has a lower spatial resolution in comparison to fMRI, the use of sLoreta supplements by identifying the strongest spatial source. This study clearly shows that EEG is a sound and workable instrument useful in similar studies, especially when facilities like fMRI are hard to acquire due to cost and availability.

Appendix

Following steps will be executed for statistical analysis of collected data.

1) Convert electrode coordinate list to get the talarich coordinate file in .sxyz format.
2) Create sLORETA transformation matrix (*.spinv) with the help of talairach coordinate file (*.sxyz).
3) Drag and drop these files (*.sxyz and *.spinv) in the "viewer" section of LORETA.
4) Drag and drop one of the ERP/EEG file and click on the ERP, at the main peak, which happens to be the visual P300.
5) Perform ERP statistical analysis in the "statistics" section of LORETA.
6) Use average referencing with 19 electrode and 200 time frames.
7) No normalization on the data is performed.
8) Select paired groups, tests A=B with no baseline correction.
9) Save the results of T test in file within the same working folder.
10) Check the Threshold and Extreme Ps file at this location. It contains the max t-value.
11) Open the ERP t test file in viewer and click on the time frame that holds the max t-value.
12) Note its time frame.
13) Convert the EEG text files into .slor by using the "EEG/ERP to sLoreta" option in Utilities section in Loreta.
14) In a fresh session of Statistics, perform the sLoreta analysis.
15) Repeat steps 7 through 9 with a few alterations. Instead of t-test, perform "log of ratio of averages (Log of F-ratio)" and instead of all time frames use the time interval around the time frame identified in step 12.
16) In a fresh session of Viewer, convert the data type to sLoreta time domain and open the sLoreta test file.

17) The Slice viewer shows the neuroanatomy of the identified correlates in terms of brodmann area number and name, talairach coordinates, and the lobe in which this brodmann area resides.

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