ABSTRACT

Information Overload: Detection and Prevention through
the Usage of Consumer Neural Devices

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Information Overload is a state in which individuals have a vast amount of information that is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation. The Information Age and growing excess of digitally available information amplifies the problem of Information Overload, which handicaps employees' productivity and well-being. This dissertation employs a non invasive customer oriented EEG sensor to explore how Information Overload affects the human brain, its executive parts and its cognitive functions and develops a theoretical mechanism for understanding the Information Overload phenomena.

Information Overload: Detection and Prevention through the Usage of Consumer Neural Devices

by

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DEDICATION

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CHAPTER ONE

Introduction

Modern organizations are operating on increasing amounts of mostly digital data and information. Available data and information grow by 40% each year. According to current estimates, the size of business related data today is 17ZB or 17 $x10^{21}$ bytes, while the total size of stored data nears 44ZB. To put this in perspective, if this amount of data is to be stored on letter size papers and stacked together, the paper stack would be 77 light years tall[1]. To compound the problem even further, organizations are now expected to handle ever-growing non-traditional data sources. The non-traditional data sources are commonly accompanied by machine generated data and by data streams collected from the sensor devices. A few decades ago, organizations were not capable of storing, processing, analyzing and ultimately understanding the ever growing amount of data. As information technology advanced, organizations eventually became able to store and process the available data. As soon as information system solutions like Decision Support Systems and Data Analytics caught up with the hardware advances, organizations started to understand the available data. The newest breakthrough in Big Data and Data Analytics is gradually allowing organizations to better use the available data. However, it is still not uncommon for organizations to operate in a state where they are faced with more data than their systems can process.

This state is defined by Speier (1999) as Information Overload (IO). The term itself was coined in 1964 by Gross (Gross 1964) and popularized in 1970 by Toffler

[1] Assuming 300 words per paper and 0.05 mm paper thickness

(Toffler 1970). Organizations are reporting limited success in mitigating this problem by implementing alternatives for searching (Lau et al. 2001; Turetken and Sharda 2001), visualizing (Turetken and Sharda 2001) or extracting content (Dale et al. 2005) from growing amounts of available data. These vast amounts of available information create spillover effects for the employees of these organizations. Information systems were always understood as a sum of software, hardware and organizational resources orchestrated together with a common goal. That goal consisted of providing as much information as possible as quickly and efficiently as possible to the organizations which employ them and to the individuals who use them. Information was understood as one of the key organizational resources. This position motivated scholars to coin the term Information Age – an age where the most important resource is information, just as the most important resource in the Industrial Age was the industrial means of production. During the constant improvements in performances and efficiencies of information systems, insufficient attention has been given to the ability of humans employed in these organizations to process the ever growing amount of available information. And since the high tech and information driven companies slowly started to dominate the business and media landscape, the vast amount of available information started to impact individuals outside the organizational boundaries.

In general an information age citizen is now swarmed with instantaneous and readily available sources of information. To illustrate this point, the average information age citizen of today processes around 122 emails per day (Radicati Group 2015). Newer communication channels and media sources are also keeping the average information age citizens constantly exposed to vast amounts of information. This exposure is so strong that an average individual uses 5.54 social network accounts, while actively participating in 4 digital social networks. On average, individuals spend 1.77 hours per day using social media. Those individuals are on average exposed to information sources from 350 connections (e.g. Facebook friends). Furthermore, individuals are required to passively read and process the information from all those sources, and they are also expected to participate. To be perceived as active by their contacts, average information age citizens are recommended to post around 2 Facebook, 3 Google+, 5 Pinterest and around 3 Twitter messages or posts per day (Buffer 2015). And the exposure to information does not stop there. The average information age citizen receives up to 40 messages per day and 12.3 voice calls per day. It is important to note that these numbers (Table 1) represent the average values across all age groups. The available data shows that older generations are in general less immersed in information systems. This lack of immersion limits their exposure to information. As a result of high levels of technology immersion, younger generations are exposed to higher amounts of information on a daily basis especially when compared to older generations. In contrast to the older generations, younger generations face the greater exposure to information technology and high information levels at a very early age. The differences seem to expand noticeably with the wider adoption of information and communication technologies characteristic for younger generations. As a result, the terms of Digital Migrants and Digital Natives are commonly used to distinguish these two population groups.

The term Digital Native is used to represent a person born or raised during the age of widely available digital technology (1980s and later). On the one hand, Digital Natives are familiar with computers and the Internet from an early age and as such are under greater exposure to the growing amount of digital information. On the other hand, Digital Migrants are individuals who were brought up before the widespread use of digital technology (before 1980s for highly industrialized countries).

Table 1: Information Exposure for Average Information Age Citizen

Source of Information Exposure	Amount				Reference
Emails processed per day	122				(Radicati Group 2015)
Social networks used	4				
Number of social networks accounts	5.54				(GWI 2015)
Time spent on Social networks	1.77 hours per day				
Number of Facebook friends	350				
"Recommended posts per day"	FB	G+	PI	TW	(Buffer 2015)
	2	3	5	3	
Texts messages per day	40				(Pew Research Center 2011, 2014)
Number of voice calls per day	12.3				

Exposure to information is thus not limited to organizations, since the growing amount of data influences individuals as well. This state in which individuals have a vast amount of information that is readily available, without mechanisms to check the validity of the content and the potential risk of misinformation (Flew 2007; Graham 1999), is known as Information Overload. This term is not necessarily exclusive to the Information Age, but the Information Age and growing amounts of digitally available information amplify the problem of information overload. The state of Information Overload is known to handicap employees' productivity and well-being. For example, the human brain works optimally only if less than seven information chunks (Miller's Law) are being actively processed or memorized. It is also known that the human brain will try to reconfigure itself in order to cope with the growing amount of information. Dishman (2014) argues that employees are prone to unconsciously discard textual information from email correspondence unless the available information pertains to the topic they are currently engaged with. Declining average memory spans in younger generations testify that the human brain also tries to cope with growing amounts of information by decreasing the length of the average attention spans. Ripples from Information Overload on individual levels also come back to haunt the organizations in which the overloaded individuals participate, even if the individual would otherwise perform exceptionally. Specifically, Information Overload negatively influences social capital formation in organizations and causes even "star employees" to fail to perform efficiently (Oldroyd and Morris 2012). This then results in less efficient business operations and decreases the overall wellbeing of the employees using information systems.

The lack of theoretical understanding, compounded with the growing negative and everyday implications, creates a case for further investigation of the Information Overload phenomena. Furthermore, recent advances in understanding the ways in which the human brain works promise a novel, unexplored and abundant data source. This data source has the potential to improve understanding of the Information Overload phenomena, means of detecting it and ideally our ability to prevent the phenomena of Information Overload altogether. However, although our understanding of the human brain and the instruments of neuroscience have advanced well beyond Miller's Law, old problems remain coupled with newer ones: most of the neural instruments are still tied to clinical environments, limiting their potential in researching real world phenomena. Most of those instruments also require participants to go through a series of uncomfortable procedures. The procedures, especially in the case of intracranial instruments, can often be very invasive. This situation generally demands a constant monitoring by the highly trained medical personnel. Even noninvasive instruments like functional magnetic resonance (fMRI) and electroencephalograph (EEG) cause a significant amount of discomfort for participants and require highly trained medical personnel to oversee the process. Additionally, clinical instruments can sometimes generate a volume of data which cannot be meaningfully processed in real time. To make it worse, most of the data is recorded from the brain functions (e.g. muscle movements, unconscious reactions, life support etc.) of little importance to information systems research. This situation represents another disadvantage for information system researchers, as there is no need to collect brain data which cannot be tied to the constructs and theories used in information systems discipline. For example, information systems are rarely concerned with motoric functions of the human body since those functions have almost no relationship to either systems or information components of information systems constructs. In order to bypass the problems of clinical settings, real time data, medical personnel and unusable data, this research tests if a mono-polar consumer oriented neural device is capable of detecting brain signals that were previously detected exclusively by clinical devices. This research also tests if the data stream from the Consumer Neural Devices (CND) can be used to detect, understand and test the Information Overload process in the human brain.

This research uses two prominent information systems theories to position the study of information overload. Those two theories are Information Richness Theory (IRT) and Information Naturalness Theory (INT). On the one hand, IRT is used to describe a communication medium's ability to reproduce the information sent over it.

According to IRT, richer communication mediums are generally more effective for communicating equivocal topics than leaner, less rich media. On the other hand, INT posits that the course of human evolution has led to the development of the brain that is designed for face to face communication. From the standpoint of INT, other means of communication are too recent to create any evolutionary changes to the human brain. Implementing communication media that limits essential elements of face-to-face communication (e.g. text), thus results in building cognitive obstacles to communication.

Ontology and semantics employed in IRT and INT are universal enough to encompass all communication and information dissemination channels used today. However, those two theories clash when it comes to selecting the best way of communicating information. This research uses the data gathered from the CND to add to this theoretical debate and to further the understanding of how the state in which a user is supplied with a growing amount of information (information influx) actually affects the user's ability to avoid Information Overload and continue handling elementary cognitive tasks (ECT).

This research uses a noninvasive mono-polar customer level electroencephalography (EEG) sensor (see Appendix A for further details) to explore how Information Overload affects information system users' ECT performance in scenarios when the user is subjected to different information influxes. Specifically, this research utilizes a CND to gather signals from the executive parts of human brain. The executive parts of the human brain support the following actions: processing elementary cognitive tasks, conducting decision making and supporting information processing. Most of the executive parts of the human brain are stationed in the pre-frontal core of the brain (PFC). This research positions a clustered 12-electrode sensor at the Fp_1-A_1 EEG system coordinates to record high and low alpha, high and low beta, gamma, theta and delta EEG frequency bands. EEG measurements are accompanied by supplemental data sources, namely participants' pulse rates and SpO_2 readings provided by the clinical grade oximeter and, where available, textual data. Heart rate and oxygen saturation measurements are used to control for undesired side effects that might distort the neural readings. These instruments and settings were used in order to record EEG readings which are known to demonstrate different states of participant's memory performance, cognitive workload, fatigue, and task difficulty.

Dissertation Potential

This research has the potential to create new IS knowledge in multiple ways and in both a direct and indirect manner. To start, this study expands the theoretical and practical understanding of a prominent technostress phenomenon and proposes a theoretical mechanism which reconciles the differences between INT and IRT. This study also expands the theoretical boundaries and understanding of the workings of the pre-frontal lobe under the state of Information Overload in real-world settings. Furthermore, this project pioneers a nonstandard data collection process based on using non-clinical neural interfaces for everyday business related purposes. This dissertation acknowledges that CND are nowhere near the capabilities of their clinical counterparts. However, this dissertation posits that Information Overload can be studied and detected using CNDs because most of the effects coming from Information Overload are known to come from the EEG coordinates used in this research. This dissertation does not posit that data resolution supplied by CNDs is in any way identical to the spatial and temporal resolution of data provided by the clinical instruments. Finally, this project builds a base for businesses to create a better and more stress-free environment for their employees.

In short, this dissertation answers the following research questions: How does Information Overload influence individual elementary task performances? What are the differences between Information Overload when it comes to Digital Natives and Digital Migrants ? How are Information Richness and media naturalness influencing ECT performances under the state of information influx? How can Consumer Neural Devices compliment clinical neural devices and expedite the information systems research? These questions are further justified in Chapter Two of this dissertation.

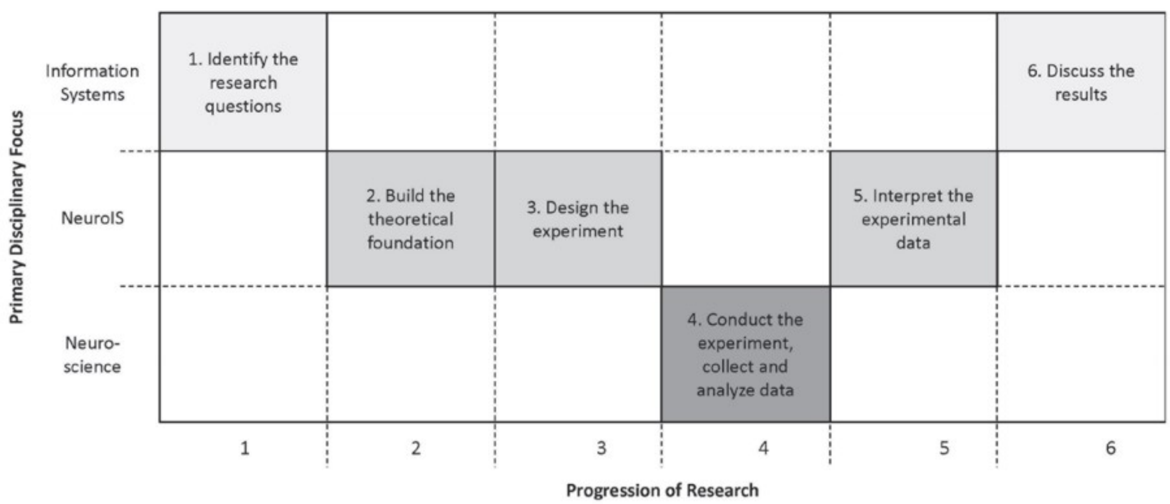


Figure 1: NeuroIS Research Framework (Vom Brocke and Liang 2014, p. 24)

I use NeuroIS research framework (vom Brocke and Liang 2014) from Figure 1 to frame my dissertation. Thus, this dissertation proceeds as follows: In Chapter Two I review two literature sections on Information Overload and NeuroIS. This literature review is followed by a sub-chapter which elaborates on IRT and INT. Chapter Two ends with explaining Theoretical Mechanism of Information Overload and the corresponding hypotheses. Chapter Three is used to illustrate the employed methodology, details the data collection process, experimental design and experimental procedures. Data analysis and discussions are presented in Chapter Four. This study ends with Chapter Five, which contains a discussion and an overview of theoretical and practical implications and limitations of the used approach.

CHAPTER TWO

Literature Review

This chapter covers methodological aspects of the literature review and two sections of literature that are crucial for understanding the foundations upon which this dissertation is built. Those two sections are Information Overload review and NeuroIS review. This chapter starts with the literature review methodology and proceeds with an overview of key publications. The first section presents an overview of Information Overload literature. The second section covers the central parts of NeuroIS research. The NeuroIS literature section is designed to acquaint the reader with the building blocks of NeuroIS, namely with the most important themes and topics in the NeuroIS field, constructs mapped to brain anatomy and the common instruments used in NeuroIS. Later parts of this chapter contain a theory literature review and a discussion on theoretical mechanisms of information overload.

A methodology of strict systematic research review is used in this dissertation. The criteria for including and excluding literature are clearly defined. The use of strict and defined protocols in this literature review is motivated by two reasons. Firstly, these protocols minimize potential author bias (Feak and Swales 2009). Moreover, they also allow complete replicability of this literature review.

The basket of Eight[1] (BoE) Information Systems journals is used as a starting point for this literature review. BoE literature is further expanded with major IS conferences (ICIS, ECIS and AMCIS) and with NeuroIS specific publication venues such

[1] For more information about BoE please consult https://goo.gl/cBy44M.

as the proceedings from the Gmunden NeuroIS retreat. Conferences were added to ensure that emerging research ideas, which might not be published in journals due to relative novelty of the field, are also considered. Once the base body of the literature is assembled, this literature review continues with forward and backward reference search. Forward reference search is understood as a process in which a researcher collects articles that cite a specific publication of interest. Backward reference search involves identifying and examining the works cited in a reviewed article. Backward search is used to examine the development of a topic and to identify authors and organizations that focus on a specific topic of research. Backward reference search is followed by a second-level backward reference search in which sources cited by the analyzed works are inspected and added to the analyzed literature. This step helps to identify potential inconsistencies in the literature. The initial search was conducted using the ABI/INFORMS database. The further searches had to go beyond the business journals in order to cover the seminal works from other disciplines – primarily from neuroscience.

In the first step of the literature review the following code was used to search the ABI/INFORMS database for works of interest to this study:

> *ab(KEYWORD) AND (pub(("MIS Quarterly" OR "Information Systems Research")) OR pub(("Journal of Management Information Systems" OR "European Journal of Information Systems")) OR pub(("Information Systems Journal" OR "Journal of the Association of Information Systems")) OR pub(("Journal of Strategic Information Systems" OR "Journal of Information Technology"))).*

The search function was performed multiple times with the following keywords: technostress, information overload, neuro*, EEG, neuroIS and experiment. These keywords were used as single keywords and in meaningful combinations with each other. Time limits for journal publication dates were not imposed. This allowed me to include earlier works as well as the recent publications. Furthermore, submissions which did not undergo peer revision were discarded. The same search procedure was used with AIS eLibrary to search through the conference proceedings. For the Gmunden NeuroIS retreats, publicly available PDF proceedings were used to supplement the database not in existence. Since Gmunden deals exclusively with NeuroIS and neuroscience concepts in general, two keywords (Neuro* and NeuroIS) were not included in this search.

This set of keywords was used for multiple reasons. One objective was to ensure that potentially diverse nomenclature for the same phenomena is not left out of the search. The keywords technostress and information overload, either on their own or in combination, allowed the inclusion of this diverse nomenclature. Moreover, this set of keywords was used to understand to what extents and in which ways are NeuroIS studies present in the field. The keywords also enabled me to detect all Information Overload studies conducted using EEG constructs. And finally, this study uses a set of EEG constructs in order to understand the phenomena of information overload. Encompassing already existing EEG studies of Information Overload is critical to establishing the borders of the current knowledge. Backward and forward searches were not limited to any keywords, but guided by the importance of the referenced works. The search results of the first step of this literature review are presented below (Table 2). These results position Information Overload as a topic of relatively low interest[2] for IS researchers. Furthermore, IS scholars were even less concerned with the phenomena of technostress. These results can serve as partial support for the introductory arguments for motivating this study. It seems that IS researchers in general have not paid much attention to

[2] For the sake of the comparison, well researched topics like IT Strategy and Knowledge Management received 350 and 239 hits in the BoE respectively. Surveys appeared in 545 BoE publications and qualitative methods in 193 BoE publications.

understating negative aspects of technology usage. The results provided in Table 2 are consistent with previous literature reviews on information overload. Specifically, as Eppler and Mengis (2004) point out, the business disciplines that have researched the Information Overload concept in peer reviewed journals the most are marketing, organizational sciences and accounting. Surprisingly, out of 168 journal publications Eppler and Mengis had analyzed, only 13 came from MIS journals. Eppler and Mengis openly expressed their surprise (p. 339) since they had initially expected that MIS field had investigated this phenomenon extensively.

Table 2: Literature search results – first step

	Keywords					
Source	Technostress	Information Overload	Neuro*	EEG	NeuroIS	Experiment
BoE	8	11	6	4	6	209
ICIS	7	20	18	3	6	610
ECIS	0	20	7	1	1	357
AMCIS	12	28	19	4	2	665
Gmunden	6	3	*	37	*	57
Total	33	82	50	49	15	1898

NeuroIS and Neuro* also scored a low number of hits. However, these results could be explained by the recent emergence of these two terms. Namely, the term NeuroIS and neuroscience in general was embraced by IS scholars for the first time in an ICIS 2007 panel. This ten year period could be one of the culprits for the low proliferation of NeuroIS topics, especially since the first BoE NeuroIS article was published in 2011. Similar logic holds for EEG based studies. It is therefore unreasonable to expect that IS scholars would include an instrument from neuroscience prior to deciding to incorporate the concepts from neuroscience into IS domains. Interestingly, not a single study had used any well established EEG metrics (e.g. (Berka et al. 2007a; Gevins and Smith 2006; Holm et al. 2009; Kramer 1990; Pope et al. 1995)) to study any form of Information overload, technostress or any of its sub constructs. An oversight of that magnitude signifies a large methodological and theoretical gap in the IS literature. It is not only that IS as a field lacks an objective methodology for encompassing and understanding this growing phenomenon but IS literature also lacks a general theory or a set of theories to understand negative aspects of technostress and Information Overload in particular. This dissertation posits that gaps of those proportions handicap our ability to understand and research important IS phenomenon. Thus, those gaps should not be left unfilled.

I have read all content related BoE, ICIS, ECIS, AMICS and Gmunden publications that appeared in the first step of the literature review. I have also inspected all methodologically related hits as well in order to expand the understanding of the experimental standards in IS discipline. Backward search resulted in 63 additional hints of interest, while the forward search added 17 additional literary resources to this study. I have analyzed all hits based on the topic coverage, synthesis of previous works, methodological contributions and general significance to the Information Overload phenomena (Feak and Swales 2009). Not a single hit was excluded due to rhetorical, structural or reasons of coherence. The rest of this sub-chapter covers Information Overload and NeuroIS literature and the most prominent themes and topics in those bodies of literature.

Information Overload

Information overload is widely understood as a state in which individuals have a vast amount of information that is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation (Speier et al. 1999). A slightly different definition of Information Overload takes into consideration the rate in which the information is presented to an individual. Specifically, it defines Information Overload as a state in which the information must be processed at a rate that exceeds the person's capacity to process the information influx within the given time (Schick et al. 1990; Tuttle and Burton 1999). Information Overload is also understood as the state of an individual in which not all information inputs can be processed and utilized. This definition is used by Jones et al. (2004). However, this approach adds an additional component to the Information Overload definition: mental breakdown as a result of information influx. Information overload is also portrayed as a state which occurs when the volume of information supply exceeds the limited human information processing capacity. This understanding of Information Overload does not include mental breakdowns, but only a set of dysfunctional effects such as stress and confusion as the result of growing information influx (Meyer 1998).

Thus, it appears that the core understanding of Information Overload is relatively congruent among different authors and disciplines. However, although the understanding of the Information Overload is congruent, an unambiguous definition that spans across disciplines is not agreed upon. As Eppler and Mengis (2000) point out, all literature review works on Information Overload take a narrow, discipline-wide approach. For example, Malhotra (1982) and Owen (1992) focus on consumer oriented research.

Schick et al. (1990) examined the accounting literature and IS evaluation scenarios. Edmunds and Morris (2000), Grise and Gallupe (1999), and Nelson (1994) approached the phenomena of Information Overload through the lenses of information systems discipline. Therefore, information systems authors focus on the Information Overload topics in environments where some form of IT was used.

Overall, the central focus of most business disciplines is to understand how the performance in elementary cognitive tasks and in the case of an individual fluctuates with the levels of information influx. Interestingly, it seems that researchers across multiple disciplines agree on one point: elementary performances of an individual using information system correlate positively with the level of information influx but only up to a certain point. When the information influx grows over that point, the elementary cognitive performances of an individual tend to decline (e.g. Chewning and Harrell 1990; Cook 1993; Griffeth et al. 1988; Schroder and etc 1967; Swain and Haka 2000)).

Information Overload Scopes

According to Butcher (1995), there are three categories which can be used to define the scope of an Information Overload study. The first category is Information Overload on individual levels. This category explores individual abilities to cope with the growing information influx. The second category tackles organizational information overload, while the third category handles Information Overload in consumers during the purchases process. This research is primarily concerned with the first category of information overload.

Information Overload Themes

Eppler et al. (2004) present a comprehensive review of Information overload. From it, the following themes were altered to fit the scope of this paper and updated with the newer IS findings. Those themes are Information Overload situations, causes, effects and countermeasures against information overload.

Information Overload-Situations. The common narrative throughout the literature recounts the situation in which Information Overload occurs. Namely, Information Overload commonly occurs in situations where individuals are exposed to an abundance of information in different forms. Those situations include Internet browsing (Berghel 1997), screening for medical information (Bawden 2001), financial analyses (Chewning and Harrell 1990), meetings (Grise and Gallupe 1999; Schick et al. 1990), email messages (Speier et al. 1999) and information analysis or processing situations in general. Information Overload is also present during different communication and decision processes. What is common for all Information Overload situations is that all those contents rely heavily on cognitive and memory performances and on the general wellbeing of an individual (i.e. fatigue).

Information Overload-Causes. When it comes to the roots of information overload, the analyzed literature set mentions multiple causes. Anatomical limitations stemming from limited processing capacity of the human brain (e.g. (Herbig and Kramer 1994) and (Dimoka, Pavlou, et al. 2010; Dimoka et al. 2012)), different performance levels caused by environmental factors (O'Reilly 1980; Owen 1992) age (Swain and Haka 2000) to unnaturalness of digital communication channels (Van Zandt 2004).

Bawden (2001), Edmunds and Morris (2000) and Schultze and Vandenbosch (1998) link Information Overload causes to storage capacities of information systems, speed of access to information, Internet, emails and other forms of digital information and communication technology. Ambiguity, novelty, intensity, quality and uncertainty of information (Schneider 1987) are also understood as causes of information overload. Finally, some causes of Information Overload extend beyond the individual categories into the domains of organizational theory and design. Since the organizational factors are beyond the scope of this literature review, those works were left out.

Information Overload-Effects. The effects of Information Overload on individuals are similarly diverse. Effects range from performance related issues (Speier et al. 1999) to more general problems like lower well-being (Conger and Kanungo 1988). Thus, it seems that Information Overload affects not only measurable individual performances, but the welfare of the overloaded individuals. Moreover, Cook (1993) points out limited search directions and noncompensatory search patterns as other effects of information overload. Also Eppler and Mengis (2004) mention overlapping and inconsistent information outputs. Bawden (2001) elaborates on ignoring information and loss of control over information. Therefore, it becomes clear that Information Overload might be a vicious circle on its own: the more information an individual has, the more misdirected, error prone and chaotic that individual becomes. Assuming constant information flows, this means that the Information Overload might manifest as a self-propelling phenomena. Sparrow (1999) links information abstraction and misinterpretation as another symptom of information overload. And Jacoby (1984) links higher time requirements and information processing delays with the state of information overload. To synthesize, the effects of Information Overload include both elementary individual performances and well being, as well as ability to interpret the coming information. Most importantly, it seems that Information Overload might results in a vicious circle of self-perpetuating negative effects on the individual level.

Information Overload-Countermeasures. The analyzed literature is abundant with propositions of countermeasures against Information Overload. Commonly mentioned countermeasures include working on individual traits like time management skills (Bawden 2001), personal information management (Edmunds and Morris 2000) or information screening skills (Van Zandt 2004). Countermeasures based on the application of information systems are also widely presented. For example, Nelson (1994) argues for natural language processing systems. Information quality filters as countermeasures are mentioned as early as 1967 (Ackoff 1967). Denning (1982) claims that making users evaluate the information is yet another countermeasure. Another prominent theme in Information overload prevention literature is the actual characteristics of the supplied information, like information quality (Allert 2001), information customization (Ansari and Mela 2003), intelligent interfaces (Bawden 2001), information simplification (Herbig and Kramer 1994), information dynamics (Jones et al. 2004), information visualization (Chan 2001), information aggregatization (Grise and Gallupe 1999) and focus on value-added information (Simpson and Prusak 1995). In summary, all countermeasures seem to include both the technical and design aspects of information systems which supplies information to the participating individuals. Literature also contains works that argue for organization and society wide countermeasures (Eppler and Mengis 2004), however those works are once again not fitting for the scope of this dissertation.

Themes Summary. To summarize, the state of Information overload in individuals can occur in multiple situations in which some form of information systems are used. The state of Information Overload can be created by a vast array of causes and it can manifest itself in varying effects. Those effects vary from trivial issues (e.g. discomfort) to more serious ones (e.g. omitting information and negative wellbeing). Information overload countermeasures range from simple training and exercising, over altering existing communication channels to designing completely new information systems.

However, the manner in which Information Overload manifests is almost identical throughout the analyzed literature. The first way is by increasing the sheer amount and influx of information, assuming the time to process the information remains constant. The second way is to decrease the available time in which an individual has to process the constant amount of information. Naturally, if the information influx increases in intensity and the time to process the available information shorten, individuals will also experience the state of information overload.

Information Overload Synthesis

The literature review section on Information Overload ends with a synthesis of the analyzed literature. In it, I distinguish between what has been accomplished and what has to be done to further the Information Overload research. Existing literature is synthesized and used to produce an updated perspective on the Information Overload topic. I also place the existing literature in a broader scholarly and historical context and reflect on the connections between different disciplines. Information Overload is understood as both individual- and organizational-level phenomena. For the purpose of this dissertation, I limit the analysis on the individual-level. In general, the Information Overload literature analyzes Information Overload effects on working professionals (i.e. IS auditors, project managers, middle and high level management) and regular individuals (i.e. email users or website visitors).

Unsurprisingly, diverse research techniques coupled with varying field standards of multiple disciplines and approaches resulted in contradictory findings regarding the information overload. Different literature themes suggest that situations in which Information Overload manifests are meticulously catalogued, yet a coherent understanding of the underlying mechanisms behind Information Overload is not explicated nor understood. Similarly, multiple Information Overload causes have been reported but an overarching explanation fitting for all causes is still missing. Measures to counter Information Overload are also underdeveloped in the literature. Specifically, the vast majority of authors were eager to provide a narrow solution to a specific subset of Information Overload effects, but not a single study analyzed the root causes of Information Overload over different topics, situations, causes and disciplines. Literature on the effects of Information Overload provides a stark contrast to the literature covering situation, causes and countermeasures of information overload. In it, authors rely heavily on findings from other disciplines like cognitive sciences and psychology to better understand the effects of information overload. Overarching concepts like individual wellbeing and performances are also present throughout the literature.

In short, it is obvious that information systems and other business disciplines have made some progress in understanding information overload. Consensus over the definition of Information Overload has not yet been reached, but a congruent narrative is beginning to take shape. This discipline spanning narrative revolves around the situations in which information influx influences individual performances is well established in multiple methodologies, topics and points in time. This situation on the field anchors the discussion and provides a robust starting ground to position further studies. However, there is still a much work to be done.

To start, it is imperative to create a unifying concept which encompasses Information Overload in an overarching manner and which spans through multiple disciplines. Currently, the existing granular understanding of isolated aspects of the phenomena are scattered throughout the literature and disciplines. That granularity handicaps the understanding of the underlying mechanisms behind information overload. And since individual cognitive performances are the main leitmotif in the analyzed literature, it might be beneficial to employ the toolsets of neuroscience to understand the underlying mechanism behind all Information Overload instances. The sole candidate for the role of those mechanisms is the human brain.

It is well established that the human brain is the primary organ that humans use for information storing, accessing and processing. Insights from the literature are univocal: Information systems can no longer afford to treat the human brain as a black box. Past experiences in which concepts from psychology or cognitive sciences have been borrowed have proven to be only partially beneficial. Limited benefits mostly stem from an inability to understand universal root causes of information overload. Furthermore, previously used research methods are also incapable of explaining causal mechanism and capturing truly objective data in a realistic environment and in real time. Thus, if our understanding of Information Overload is to advance, we have to depart from traditional research methods like surveys, qualitative interviews, formal modeling methods and case studies.

That is why this chapter continues with a brief literature review of NeuroIS. In it, an overview of NeuroIS literature is presented and accompanied with a concise overview of research construct coming from the brain anatomy and research methods used in NeuroIS.

NeuroIS Literature Review

Neuroscience (or neurobiology) is the scientific study of the nervous system. NeuroIS combines neuroscience with Information Systems. As such, NeuroIS is understood as a field in the Information Systems discipline that relies heavily on neurophysiological tools and knowledge to deepen the development, adoption and impact of information and communication technologies. The formalization of NeuroIS as a field of IS research was championed by Prof. Pavlou, Prof. Davis and Prof. Dimoka at ICIS 2007 in Melbourne, Australia (Pavlou et al. 2007). As the field progressed and as the number of NeuroIS scholars grew, the need for a specialized NeuroIS venue became evident. The Melbourne gathering of IS scholars led to the inaugural Gmunden IS retreat in 2009, which transformed into the premier global NeuroIS conference. Beginning in 2009, the Gmunden NeuroIS retreat was held in Gmunden, Austria, on an annual basis. Creating NeuroIS allowed IS scholars to combine the social sciences with theories and tools of neuroscience and neurophysiology. Ideally, this coupling enables social scientists to examine various social phenomena with neuroimaging instruments.

Neuroscience in general and cognitive neuroscience in particular focus on examining the brain mechanisms underlying mental processes. Cognitive neuroscience has a proven record of propelling multiple social science disciplines towards new advances. The most prominent advances have been made in neuroeconomics (i.e. Aimone and Houser 2016), neuromarketing (i.e. Ariely and Berns 2010) and psychology. As Pavlou et al. (2007) point out, IS research is still largely unaware of those advances. While economics, marketing, and psychology have already grasped the potential of cognitive neuroscience and functional neuroimaging, IS researchers are still hesitant to consider how cognitive neuroscience can be used to augment IS theories. However, although a wide proliferation of neural methods has not occurred in the IS field yet, first steps toward including neural constructs are already happening.

Specifically, NeuroIS has been used to enrich IS research and a number of relatively recent research findings occurred as a result. For instance, NeuroIS has been used to explore multiple issues, ranging from effects of technostress (Tams 2014), information processing biases in virtual teams (Minas et al. 2014a), through effects of emotional states on financial trading decisions (Astor et al. 2013), measures of risk perception to predict information security behavior (Vance et al. 2014) and complementing business process modeling tools (Shitkova et al. 2014). Most of the BoE papers, however, approach NeuroIS from conceptual and research policy driven grounds. Reflections on the Gmunden Retreat from 2009 (Riedl, R. D. Banker, et al. 2010) re-defined what NeuroIS is, which tools are relevant for NeuroIS, what IS can learn from neuroscience and what were the current challenges for NeuroIS at that time. The results of the subsequent retreats grew in diversity, breadth and length. Thus, the findings of the subsequent retreats were not published as journal papers, but as separate proceedings – similar to established IS conferences.

IS scholars are also starting to lay out theoretical and methodological grounds on which future theory-rich research can be built. A special JAIS issues on Methods, Tools, and Measurement in NeuroIS Research (Iss.10, 2014) serves as an explicit proof of that. A research commentary (Dimoka, Pavlou, et al. 2010) illustrated the potential of cognitive neuroscience for IS research, especially when it comes to localizing the neural correlates of IS constructs, capturing hidden mental processes and challenging assumptions and enhancing IS theories. Vom Brocke and Liang (2014) also contributed to the discipline with a set of guidelines for NeuroIS studies. Those guidelines are designed to help researchers better understand phases typical for NeuroIS research and to guide NeuroIS research through the emerging standards of the discipline. Tams et al. (2014) use a technostress study to illustrate the holistic effects that come from using neurosciences and self reported data in tandem. Tams et al. improve~~d~~ our understanding of triangulating different sources of data by showing the scenario in which different measures can constitute as alternative and/or complements in the prediction of theoretically-related outcomes. Specifically, Tams et al. demonstrate~~d~~ that physiological and psychological measures can actually lead to divergent findings. Furthermore, Gregor et al. (2014) develop a nomological network with an overarching view of relationships among emotions and common constructs of interest in NeuroIS research. Finally, Müller-Putz et al. (2015) venture~~d~~ deeply into the foundations, measurements and application of electroencephalography in IS. Through their work, Müller-Putz et al. equip prospective NeuroIS researchers with solid methodological foundations for conducting EEG - based research.

Although NeuroIS continues to prove its value by expanding the knowledge on multiple IS related phenomena, and although sound theoretical and methodological foundations of NeuroIS have been laid out, many IS researchers still feel reluctant to incorporate cognitive neuroscience in their research. Some are turned away by significant resources required to conduct a NeuroIS study (Dimoka et al. 2012), while others are discouraged by the sheer breadth of non – IS knowledge required to successfully conduct a state of the art NeuroIS experiment (Müller-Putz et al. 2015a). For example, NeuroIS scholarship requires researchers to select a proper instrument and equipment that will adequately detect all elicited aspects of researched phenomena, create and maintain all required parameters for the instrument to operate optimally and finally to analyze the readings from the clinical grade neural interfaces (vom Brocke and Liang 2014; Müller-Putz et al. 2015a; Tams et al. 2014). Few IS researchers are properly trained to conduct those studies and some can be deterred by administrative hurdles required to conduct medical-grade research on human subjects. Therefore, these factors combine to prevent NeuroIS from becoming one of the dominant areas of IS research.

Additionally, preconceived notions of complexity, discomfort, ambiguity and dangers (Engber 2016; Piore 2015) of neural instruments may also be the culprits for relatively low proliferation of neural technologies outside the academia. Specifically, it has been known for four decades that the human brain can communicate directly to computers via brain to computer interfaces (Kübler et al. 2001), yet proliferation of those interfaces in IS never happened. Moreover, a similar scenario holds for the most basic customer-oriented neural sensors. Companies like Emotiv, Neurosky and Microsoft are known to work on neural sensors (Riedl, Banker, et al. 2010) and multiple EEG-based products are even available to a wide consumer audience. Yet despite the diverse and growing arguments in favor of incorporating neural devices, IS practitioners and research are still not embracing NeuroIS to its fullest extent.

In order to synthesize the existing themes and topics in NeuroIS and the most common neural instruments, this literature review proceeds with a rough overview of still nascent NeuroIS literature, as well as an overview of constructs based on the brain anatomy and functions. Finally, this sub-chapter ends with a review of most common NeuroIS instruments and maps their usage to the specific constructs and parts of the human brain.

NeuroIS Themes

The Table 3 provides an overview of BoE NeuroIS literature. My literature review returned similar results to the ones observed by Quazilbash and Asif (2017). However for the purposes of this study, I have structured the NeuroIS literature not only according to topics and outlets, but also according to themes and methods. I understand topics as matters dealt with in a journal publication. I define themes as a group of thematically similar topics. By structuring the literature in this way, as presented in the Table 3, a better insight into the state and structure of the discipline can be gained.

To begin with, the biggest cluster of papers (seven papers) is a cluster in which each paper employs some form of EEG artifacts. Kuan et al. (2014) is one of the pioneering studies in using EEG constructs for IS research. They use Emotiv EPOC 14-channel (AF3/4, F7/8, F3/4, FC5/6, T7/8, P7/8, and 01/2) wireless EEG CND to study social influence in group buying. Their study elaborates the different roles played by informational and normative social influence in affecting attitude, intention, and emotion.

Li et al. 2014 uses identical wireless EEG CND to prove that cognitive-related gaming elements, like game complexity and game familiarity, influence the density of theta oscillations. Another BoE EEG study comes from de Guinea et al. (2014). In it, the authors prove that implicit neurophysiological states (i.e. memory load and distraction) and explicit states (i.e. engagement and frustration) antecedents interact in the formation of perceived usefulness and perceived ease of use. Guinea et al. also follows the EEG reporting protocols to the letter, by reporting the type of equipment (B-Alert X10 device from Advance Brain Monitoring) and the exact EEG coordinates (F3, F4, Fz, C3, C4, Cz, P3, P4, and POz). Hu et al. 2015 rely on 65 sintered silver silver-chloride EEG system to study self control in security violations. They discover that the left and right hemispheres of the human brain were involved in security related decision making, and that the participants with low self-control had lower levels of neural recruitment in both brain hemispheres relative to those with high self-control. Gregor et al. (2014) is another study which uses EEG. This study uses EEG to demonstrate that neural correlates have predictive power for an emotion related outcome such as e-loyalty. Contrary to the established EEG protocol requirements, Gregor et al. did not provide a detailed overview of the used EEG instrument and EEG electrode coordinates. Vance et al. (2014) used the P300 component of an event-related potential, which is also a well-known EEG construct. Using the Iowa Gambling Task, a widely used technique shown to be correlated with real-world risky behaviors, they show that the differences in neural responses to positive and negative feedback strongly predict users' information security behavior. Minas et al. (2014) is another NeuroIS study conducted using Emotiv EPOC 14-channel wireless EEG CND to research information processing bias. This study shows that team members focus their cognitive resources on factual and normative information that supports their pre-discussion preferences, rather than deeply considering information that challenges them.

The second largest methods cluster consists of papers that elaborate on the neurophysiological methods that can complement NeuroIS research. This cluster encompasses four papers. Riedl et al. (2014) argue that six factors are central for a rigorous NeuroIS research methodology. These factors are reliability, validity, sensitivity, diagnosticity, objectivity, and intrusiveness of a measurement instrument. Tams et al. (2014) set to explore whether NeuroIS and psychometrics/psychological methods constitute alternatives or complements. They found that the physiological stress measure (i.e. salivary alpha-amylase) explains and predicts variance in performance on the computer-based task over and above the prediction afforded by the self-reported stress measure, thus concluding that NeuroIS plays a critical complementary role in IS research. Léger et al. (2014) introduces eye-fixation related potential method to the NeuroIS set of methods. Dimoka's (2012) exhaustive work on functional magnetic resonance imaging also belongs to the methodological set of NeuroIS papers.

The third largest cluster explores conceptual NeuroIS issues. These issues start from specific design guidelines on how biofeedback can be integrated into information systems (Astor et al. 2013), through a set of recommendations for using neurophysiological tools in IS research (Dimoka et al. 2012) and ending in guidelines on how to conduct a NeuroIS study (vom Brocke and Liang 2014). The remaining papers are either editorial papers or papers that employ different neural instruments like functional magnetic resonance, skin conductivity, heart rate or eye tracking. Interestingly, methods like skin conductivity or heart rate tracking are not necessarily neurophysiological in nature, yet IS community understands those studies as parts of the NeuroIS literature. For example, Anderson et al. (2016) use eye tracking to show that eye movement-based memory (EMM) effect is a result of habituation to security messages – a phenomenon in which users unconsciously scrutinize stimuli that they have previously seen less than other stimuli. Anderson et al. also show that after only a few exposures to a warning, this neural aspect of habituation sets in rapidly, and continues with further repetitions. Teubner et al. (2015) uses a similar non-neural method of skin conductance response to study the impact of agency on human bidders' affective processes and bidding behavior in an electronic auction environment. They use skin conductance response and heart rate measurements as proxies for the immediate emotions and overall arousal of participating bidders in a lab experiment with human and computerized counterparts. Their results show that digital agents mitigated the intensity of bidders' emotions in response to auction events as well as the bidders' overall arousal levels during the auction.

When it comes to literature themes, cognitive neuroscience seems to be the most prominent one (i.e. Anderson et al. 2016; de Guinea et al. 2014; Hu et al. 2015; Li et al. 2014). This means that one of the central points of NeuroIS research have been focused on the cognitive functions of the human brain. Second most prominent theme was based on understanding human emotions by using a set neural correlates or by building conceptual bases for importing neural correlates to human emotion (i.e. Astor et al. 2013; Gregor et al. 2014; Teubner et al. 2015). How-to (Dimoka et al. 2012; Léger et al. 2014; Tams et al. 2014) and high level concept papers (vom Brocke and Liang 2014; Dimoka et al. 2012; Riedl, Davis, et al. 2014) have been equally present. The remaining clusters are smaller in size. For example, Belanger (2015) and Dimoka (2015) are two papers which provide a set of future research directions for NeuroIS field.

Alongside presenting issues like using neural constructs to better understand topics like information strategy and decision making, Dimoka (2015) also argues that IS should employ neural constructs for studying information and cognitive overload in the brain, designing IT systems that can detect and prevent Information Overload and finally to refine information systems based on their effects on brain activity. Kuan et al. (2014) and Riedl (2014) use EEG and fMRI respectively to understand the social dimension of using information systems in online shopping and human-avatar interaction scenarios. Kuan et al. (2014) pioneers the usage of multi-polar neural recordings coming from non-invasive EEG instruments that are marketed for semi professional and consumer use (Emotiv Epoch headband). Their work cements the path towards using non-clinical devices in NeuroIS field, since they have proven that even the neural constructs from non clinical devices can serve as an acceptable method of producing IS theories. This path is latter followed by multiple multi-polar CND studies (i.e. de Guinea et al. 2014; Li et al. 2014; Minas et al. 2014).

Table 3: BoE NeuroIS Literature

Paper	Topic	Theme	Method	Jour.
Anderson et al. 2016	Response to security messages	Cognitive neuroscience	ET	EJIS
Li et al. 2014	Engagement in online gaming		EEG	JMIS
de Guinea et al. 2014	Perceived ease of use and usefulness		EEG	JMIS
Hu et al. 2015	Self-control in security violations		EEG	JMIS
Teubner et al. 2015	Emotions and bidding in e-auctions	Emotional response	SCR, HR	JAIS
Gregor et al. 2014	Emotions in IS		EEG	JMIS
Astor et al. 2013	Emotional regulation in financial decisions		Conceptual	JMIS
Riedl et al. 2014	NeuroIS methodology	High Level Concepts	Methods	JAIS
vom Brocke and Liang 2014	NeuroIS guidelines		Conceptual	JMIS
Dimoka et al. 2012	Use of Neurophysiological tools in IS		Conceptual	MISQ
Tams et al. 2014	NeuroIS for Technostress	How-To	Methods	JAIS
Léger et al. 2014	Application of EFRP to IS research		Methods	JAIS
Dimoka 2012	How to conduct fMRI studies		Methods	MISQ
Vance et al. 2014	Disregard of security warnings	Decision making	EEG	JAIS
Minas et al. 2014	Information processing bias		EEG	JMIS
Belanger and Xu 2015	Editorial on NeuroIS potential	Future directions	Editorial	ISJ
Dimoka et al. 2011	NeuroIS potential		Comment	ISR
Riedl et al. 2014	Human-avatar interaction	Social processes	fMRI	JMIS
Kuan et al. 2014	Social influence in group-buying		EEG	JMIS
Goes 2013	IS research and behavioral economics	Misc.	Editorial	MISQ
Davern et al. 2012	Historical analysis		Review	JAIS

Although BoE provides a solid overview of how-to methods, one of the seminal how-to papers was not published in the BoE but in the Communications of the AIS journal. In it, Müller-Putz et al. (2015) give an extensive set of technical instruction on how to use EEG artifacts in IS research. Their paper provides high level conceptual details about experimental procedures and protocols and builds on mapping neural constructs and correlates to specific wavelengths of the brain activity.

My dissertation now proceeds with a brief overview on brain anatomy and functions. The primary purpose of the following section is to acquaint the reader with the basic anatomical and functional characteristics of the human brain with the intention of mapping neural constructs and correlates to specific parts of the brain on the one hand and to the specific neural instruments on the other.

Brain Functions and Anatomy

Understanding of the anatomy of the human brain has progressed drastically in the late 20th and early 21st century (Anderson 2014; Bear et al. 2015; Carter and Shieh 2015; Felten et al. 2015). The historically popular concepts like phrenology, which were initially understood as scientific, were proven to be pseudoscientific and the understanding of the inner working of the human brain was revolutionized. One of the biggest contributors in understanding how the human brain operates was the introduction of the neural imaging instruments like functional magnetic resonance and electroencephalography. Those instruments enabled neuroscientists to use high spatial and temporal resolutions to understand which parts of the brain “light up” under specific experimental stimuli (Carter and Shieh 2015). Detailed maps of the human brain were presented by Bear et al. (2015, p.223-p.224) and represented in the figure below. This research uses those maps to provide an overview of the current understanding of the anatomy of the human brain and to map functional areas of the brain to potential neural constructs. According to medical conventions, the cerebrum of the brain is divided into lobes. The lobes are named after the bones of the skull that are positioned above them. Part of the brain known as the central sulcus divides the frontal lobe from the parietal lobe. The occipital lobe is positioned at the back of the cerebrum. The lower part of the brain is known as temporal lobe.

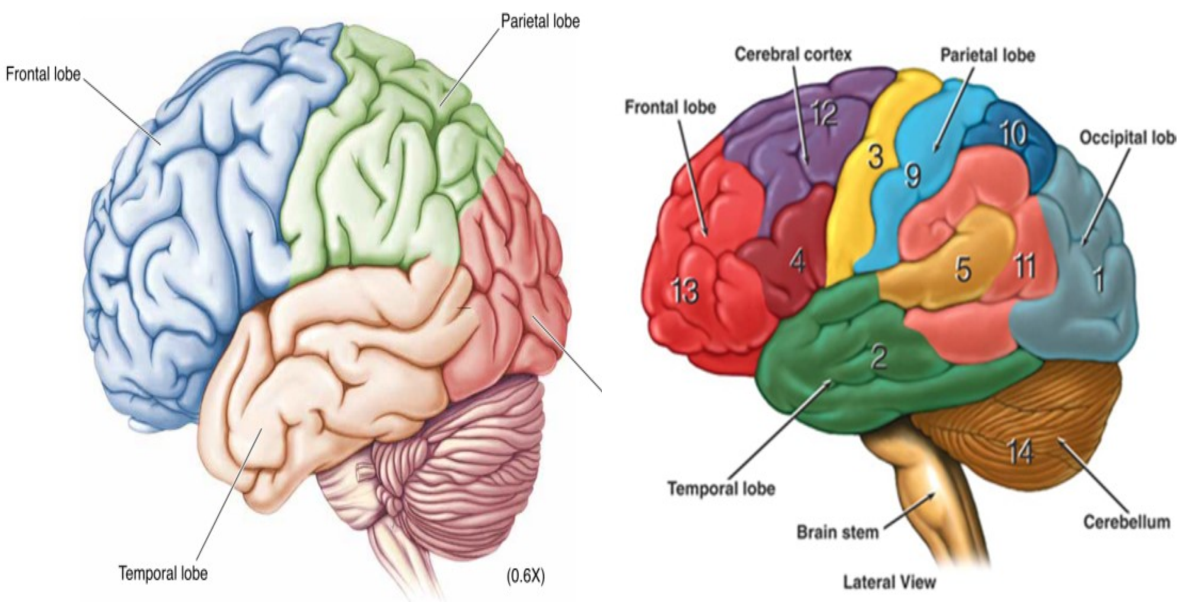


Figure 2: Brain Anatomy

Each lobe contains a set of functional areas. Those areas differ from one another based on the function they perform and on the microscopic structures that can be found within them. The frontal lobe (marked with 13) is correlated with higher mental functions and cognitive processes. Those functions and processes are used during concentration, planning, judgment, emotional expressions, creativity and inhibition activities. Cerebral cortex of the frontal lobe (12) regulates eye movement and orientation. The Broca's Area (4) operates muscles of speech, while motor function area serves for initiation of voluntary muscles. The parietal lobe contains sensory area (9) which process sensation from muscles and skin; and somatosensory association area which evaluates the feeling of weight, texture, temperature and serves as object recognition center. Occipatial spelling lobe (1) processes sight, image recognition and image perception. The Wernickes' area (11) analyzes written and spoken language comprehension. The temporal lobe (2) serves as an association area. In it, short term memory, equilibrium and emotions are being processed.

Information systems as a discipline studies people, technology, organizations, and the relationships among them. Information systems as a discipline generally understand humans as rational agents who use their intellectual abilities to employ technology inside organizations in order to augment human decision making capabilities. These intellectual abilities are almost exclusively based on the cognitive processes in PFC. Therefore most of, if not all, the brain areas that can be useful for producing IS knowledge are mapped in the frontal lobe of the human brain. At its current state and to the best of my knowledge, the information systems discipline does not express the desire to use the constructs stemming from the other brain lobes. For example, information systems research did not approach any constructs that build on human motorics, fear or automatic life sustaining process in human brain. This research now proceeds with the review of neural instruments found in the analyzed literature.

Instruments used in NeuroIS

NeuroIS frequently borrows data collection instruments from the neuroscience. Early research works in NeuroIS (e.g. Dimoka, Banker, et al. 2010; Pavlou et al. 2007; Riedl, R. Banker, et al. 2010) relied on the direct expertise of formally trained neuroscientists. However, in later works (i.e. most of BoE Neuro* hits) it was not uncommon for formally trained IS researchers to adopt a neuroscience data collection method and instruments without actually having any sort of formal training in neuroscience[3]. This research understands the trend of IS researchers using instruments from the neuroscience as a clear sign that sections of the IS community are slowly starting to feel comfortable using neural instruments in their work and without the supervision from the neuroscientists. This section of the literature review therefore summarizes the position NeuroIS literature has taken on neurophysiological tools. Also, it provides an overview of different neural tools used in throughout the literature.

Position Towards Neurophysiological Tools. To begin with, NeuroIS studies ought to consider which neural device will be used to collect data from. Human behavior is understood as a complex set of different processes and activities. Throughout the literature, those processes and activities range from unconscious variations of emotional reactions to decision-making activities which are based on cognition and conscious thoughts. As Dimoka et al. (2012 p.680) point out "neurophysiological tools enable the measurement of human responses when people engage in various activities, such as decision making, or react to various stimuli, such as IT interfaces." Most of those human behavior responses can also be captured by self-reported instruments like interview or surveys. It is widely believed that the data coming from the specific neurophysiological

[3] Most of the BoE NeuroIS authors did not have a neuroscience training component in their publicly available vitas.

device has higher levels of objectivity. Furthermore, data sets from the neurophysiological recordings also testify that neurophysiological tools can in general provide us with abundance of data that vastly surpasses in size the conventional datasets that have been gathered using the self reported techniques.

Although the NeuroIS literature does not explicate the preference towards one specific form of data collection (i.e. self reported vs. neurophysiological), the literature synthesis points out towards one unambiguous conclusion: NeuroIS studies should triangulate self-reported data with the data coming from a neural sensor. For example, Kuan et al. 2014 use a semi-professional EEG sensor to study social influence in a group-buying process. Their study did not rely solely on the neurophysiological metrics. On the contrary, it combined the self reported data (e.g. demographics and preferences) with system data, coming from the used software solution, which was combined with the neural readings from the sensor. Similar patterns can be found in all BoE NeuroIS studies where some form of neural data was collected.

Thus it can be concluded that NeuroIS literature does not position neurophysiological tools as a substitute, but as a complement to existing data collection methods. NeuroIS literature also indirectly advocates that all NeuroIS research should be designed in the way where participants are asked to self report specific data points. Those data points range from socio-demographic data to subjective personal characteristics of the participants pertaining to the study (e.g. motivation and engagement).

Neurophysiological Tools. The NeuroIS literature review presented in the introductory part of this sub-chapter provides an overview of the neurophysiologic tools and methods that were used in the BoE NeuroIS works. Although the most common tool was electroencephalography, tools like skin conductance response, heart rate, eye-tracking and functional magnetic resonance were also used. Conference proceedings add galvanic skin conductance, saliva analysis and facial electromyography to the pool of used methods. Unsurprisingly, most of these tools were believed (Dimoka et al. 2012) to be able to complement IS research. The only tool that was not initially understood as complementary to IS research is saliva testing. This review now proceeds with providing a short overview of the most common tools used in the NeuroIS literature.

Electroencephalography: Electroencephalography (EEG) belongs to the neuroimaging techniques which are used to measure electrical activity generated by the brain (Müller-Putz et al. 2015a). EEG systems use a set of portable sensors which are mounted on the scalp surface using conductive gels. The functioning principles of EEG electrodes and the 10-20 system of the positioning of the electrodes are presented in the figure below (Figure 3). Essentially, EEG in its purest form creates an electric circuit that consists of at least one sensor and one grounding electrode, mono-polar systems, or multiple sensors and one grounding electrode (multi-polar systems). The electric signals which come from the portable sensors (nodes) are amplified and processed to remove potential noise signals (e.g. eye movement). EEG detects the electrical activity of the human brain. In particular, this tool is known to reveal neuro-electrical mechanisms of the human brain. These mechanism are monitored to detect cognitive workload and task difficulty (Berka et al. 2007a; Gevins and Smith 2006; Holm et al. 2009), memory performance (Kramer 1990; Pope et al. 1995) and cognitive processes (Bartholow and Amodio 2009; Knyazev and Slobodskaya 2003).

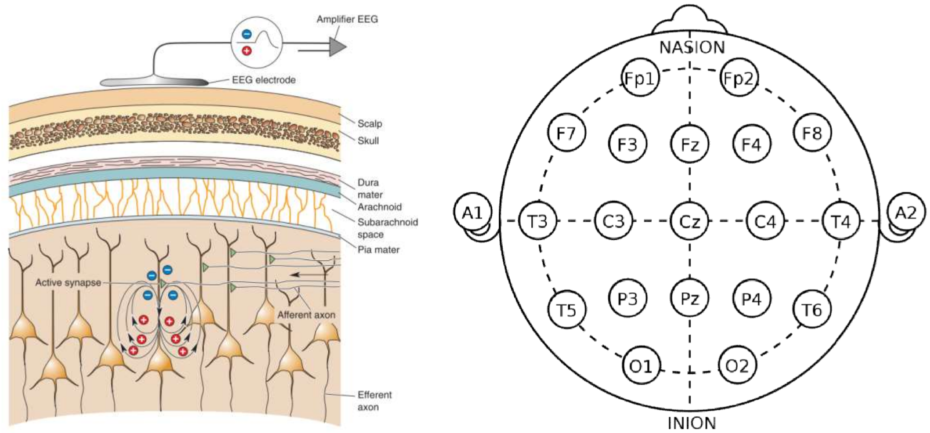


Figure 3: EEG working principle and 10-20 map

Since the readings of intracranial electrical activities from the EEG are directly connected to the central concepts of IS like memory performance, cognitive efforts, information fatigue and etc., it is no wonder that EEG is the most widely used tool in the NeuroIS literature. As of 2016, there are seven EEG based BoE studies. Those studies used EEG to explore engagement in online gaming (Li et al. 2014), differences between perceived ease of use and usefulness (de Guinea et al. 2014), self-control in security violations (Hu et al. 2015), emotions displayed throughout the use of IS (Gregor et al. 2014), reactions to security warnings (Vance et al. 2014), information processing bias (Minas et al. 2014) and social influence in group buying (Kuan et al. 2014). EEG-based methods were also used in multiple ICIS (2012 and 2014) and ECIS (2014) proceedings. EEG tools are present throughout every single Gmunden proceeding. Intriguingly, EEG is the only neurophysiologic method which also employed a device oriented towards the consumer markets (e.g. Kuan et al. 2014).

Eye tracking: Eye tracking focuses on using cameras to measure the location of eye pupil, eye movements and pupil dilation (Dimoka et al. 2012). Vast parts of the human brain are used to processes visual cues (Bear et al. 2015). The human brain is also evolutionary fine-tuned to control eye movement. Thus, eye tracking tools can be useful in research that centers on IS concepts like consumer technology, websites, social interactions through technology, online payments, IT security and video games.

There are two ways in which eye tracking have been used in the NeuroIS literature. The first one relies on collecting information on gaze position from an eye tracking device (e.g. Xu et al. 2011). Monitoring pupil dilation is the second one (e.g. Buetnerr 2016). The diameter of the pupil dilation can provide the researchers with insights into arousal and stress levels. Unlike gaze position, pupil dilation is an autonomic process and it cannot be consciously controlled. The BoE literature contains only one eye tracking work (Anderson et al. 2016). This security-centered study uses an eye tracking device to collect gaze positions. All Gmunden proceedings refer to eye tracking either directly (listed as a potential tool in a conceptual paper) or as a data collection tool in a particular study (e.g. (Gwidzka 2016) and (Buetnerr 2016).

Galvanic skin response: Galvanic skin response (SCR) measures the levels of sweat secretion from sweat glands in human skin. SCR employs electrodes that are positioned on the palmar side of the second phalanx of the first and second fingers. Those electrodes send a small electric current in order to capture the sweating levels (Jacob and Karn 2003). The higher the sweating level is, the higher the skin conductivity will be. When the participating individual is exposed to emotional stimuli, higher sweat levels are expected to occur. Furthermore, the parts of the brain which control subconscious emotional reaction are deeper and positioned in the parts of the brain developed in the early evolutionary processes. These parts are generally known as older brain structures.

This renders galvanic skin response complementary to EEG instruments, especially since EEG monitors cognitive and emotional processes that are handled by the newer and more accessible brain parts. Galvanic skin response was never used as a method in any of the BoE papers. However, this neurophysiological tool was used in one AMCIS 2015 work and in multiple works presented at the Gmunden retreats of 2011, 2012, 2013 and 2016.

Functional Magnetic resonance: fMRI is a noninvasive brain imaging method that measures differences in blood oxygenation to reflect neural activity (Felten et al. 2015). Neural activity in a specific brain area results in an increase in blood oxygenation, generally peaking around 4 or 5 seconds after the start of neural activity (Dimoka et al. 2012). According to Dimoka et al. the ability of fMRI to localize brain activity is useful to IS researchers because it is able to map experimental stimuli to the specific part of the brain with high accuracy. This allows IS researchers to better understand which stimuli activate the specific part of the brain, which further enables them to build the causal link between IS concepts and brain functions. The high spatial and temporal resolution of fMRI allows it to be used for any potential concept that is mapped to the specific part of the human brain and of interest to IS scholars. However, prohibitive factors like cost and required expertise could be inhibiting to smaller institutions.

When it comes to IS research that use fMRI, there is only one BoE study (Riedl et al. 2014) which uses fMRI to understand collaboration effectiveness of human-avatar interactions. fMRI was used to research trust in human-avatar interactions, social networking sites and customer impulsiveness in multiple ICIS proceedings (2011,2013, 2014). Finally, every single Gmunden proceeding contains at least one fMRI paper.

Table 4: Neurophysiological tools

Tool	How it works	Characteristics	Potential IS applications
EEG	It creates a closed electric circuit to detect electrical current in the brain caused by dendritic activity.	Widely used, cheaper than fMRI/PET, partial tolerance to movement, silent. Low spatial resolution, insensitive to the activity coming from deeper brain areas.	Mental load, affective and cognitive processes, positive and negative effects, memory performance, cognitive workload, task difficulty, fatigue, attention, arousal, hedonic preferences
Eye Tracking	Tracks eye gaze and eye retina using a set of cameras or a single camera	Clear visualization, beyond self-reported measures. Does not capture peripheral vision.	Web usability, search efficiency, GUI design, medium effectiveness, stress, arousal, information fixation
GSR	Voltage or resistance difference among two electrodes placed on human skin.	Low cost, minimal intervention. Lack of predictable measurement. Habituation effects.	Arousal, excitement, fear, emotion, and attention
fMRI	Uses strong magnetic field to visualize the blood flow inside the human brain.	Widely used, well developed statistical standards. Low temporal resolution.	Mapping IS constructs and stimuli to a particular brain area.
Oximeter (heart rate)	Emits light through a translucent part of the human body to measure heart rate and oxygen saturation	Low cost, wide accessibility, minimal invasiveness. Interpretation and control problems – too many factors can influence heart rate.	Arousal, joy, emotional arousal, stress, control for physical activity and medical condition
EKG	Records electrical activity coming from the heart		
Saliva analysis	Laboratory analysis of saliva.	Widely used, easily outsourced.	Polymorphisms linked to aggression and violence, stress levels
Facial electromy - ography	Measures muscle activity by recording electrical impulses that are generated when face muscles contract	High precision, real time, minimally intrusive, inexpensive. Limited to small number of muscles and low spatial resolution.	Emotional reactions, mood states, positive and negative reactions, confusion, situation awareness.

Summary: Table 4 provides a concise overview of the neurophysiological instruments, their most important characteristics and the manner in which they were used in the literature. For an exhaustive and comprehensive overview of the Neurophysiological tools, the reader is referred to the following sources: Guide to Research Techniques in Neuroscience (Carter and Shieh 2015) and Computational Neuroscience and Cognitive Modeling (Anderson 2014). Another excellent source for understanding NeuroIS perspective on neurophysiological tools in provided in the Research Agenda for NeuroIS (Dimoka et al. 2012)

Theory Literature Review

This sub-chapter provides an overview of two established theories, Information Richness Theory (IRT) and Information Naturalness Theory (INT), used to explain the mechanisms by which information is understood, processed and transmitted by individuals inside organizations. IRT and INT are also known as Media Richness Theory and Media Naturalness Theory respectively. Both theories have been applied at the individual and organizational level. IRT is positioned as a theory which takes a behavioral approach to explaining the ability of information to change the understanding within a time interval. In particular, Daft and Lengel (1986) assume that organizations collect and process information in order to reduce uncertainty. As information is processed and analyzed, the environment for making decisions can become less uncertain and less unequivocal as time passes. This theory also suggests that the fit between the communication task and the used medium is crucial: the complex tasks are better suited for richer media, while the leaner media fits simple tasks better. IRT originated at the organizational level (Daft and Lengel 1986) yet later works use it at both individual and organizational levels (e.g. Dennis and Kinney 1998). However, IRT was critiqued on its lack of biological and evolutionary basis (Kock 2002). This critique was eventually developed into INT (Kock 2004). INT takes a Darwinian stance (Kock 2004) and argues that the human species had evolved to process the more natural information (i.e. face-to-face communication) more efficiently. As such, INT takes an individual-level stance. INT thus takes a perspective close to that of cognitive neuroscience arguing that the human brain simply did not have enough time to evolve from focusing on processing the predominant face-to-face communication to more recent forms of communication.

As I discuss in Chapter One, the average information age citizen is overloaded with vast amounts of digital information. This volume of information comes from different sources (i.e. individual and/or organizational activities) and is very heterogeneous in its nature and form. Thus, I argue that a theoretical framework for understanding how mechanism of Information Overload works has to be built on the foundations set by IRT and INT. On the one hand, IRT provides the base to theorize how information fit and richness can influence the effectiveness of communication and information dissemination; while INT creates the base on which neuro-cognitive aspects can be included into the theoretical mechanism.

I also use IRT and INT to frame this dissertation and to link its findings to the ongoing discussion between these two theories. Without the underlying mechanism to ground the narrative, it would be impossible to create theoretically compelling arguments and to extend the understanding of how an average information age citizen handles different Information Overload situations. After giving an overview of both theories, I then provide a summary of key characteristics from both theories.

Information Richness Theory

Information Richness Theory (IRT) was developed as a framework to explain a communication medium's capability to transmit the information sent over it. This theory was introduced by Daft and Lengel (1986) as an addition to the information processing theory. In particular, the central premise of information processing theory states that humans process the information they receive from the environment, rather than merely responding to environmental stimuli. Daft and Lengel further augment this theory by ranking different forms of information and organizational communication based on two forces that influence information processing. Those two forces are equivocality and uncertainty. They understand uncertainty as a measure of organization's ignorance "of a value for a variable in the space". Therefore, in situations when uncertainty is low, the organization poses the data that answers the variable-related questions. High uncertainty motivates further acquisitions of objective information about the world. Moreover, Daft and Lengel stipulate that equivocality is "similar to uncertainty, but with a twist" (p. 554). They further define this force as a "measure of the organization's ignorance of whether a variable exists in the space" (p. 557). In other words, when message is equivocal it is unclear and more difficult for individuals to process it. Vice versa, when the organization is able to define which questions to ask, the equicovoality is low. Unlike uncertainty, equivocality motivates the exchange of predefined views among managers. This exchange is designed to resolve conflicts and define problems through a set of shared interpretations.

To illustrate the central points of IRT, its authors provide a two dimensional framework (p.557) with equivocality and uncertainty as the defining dimensions. This framework categorizes four different scenarios that can occur as combinations of high and low levels of equivocality and uncertainty. In this framework, low equivocality and low uncertainty define a clear situation, while high equivocality and high uncertainty mark ambiguous situations. Lengel and Daft also supply exhaustive description of all potential framework scenarios and argue that an organizational structure can be provided to facilitate equivocality reduction and/or to reduce uncertainty.

The authors further argue that the critical factor in reducing equivocality is "the extents to which structural mechanisms facilitate the processing of rich information" (p. 559). They define Information Richness as the ability of information to change individual's understanding within a specified time interval. The information which can change understanding in a time-efficient manner is defined as rich. The information that requires a long time to enable understanding is considered as "lower in richness". Lengel and Daft also provide an example of multiple media channels in order of decreasing richness: face-to-face, telephone, personal documents such as letters or memos, impersonal written documents, and numeric documents. In short, Information Richness is understood as a function of the communication medium's ability to handle multiple information cues simultaneously, facilitate rapid feedback, establish a personal focus, and utilize natural language (Lengel and Daft 1989).

Daft and Lengel (1986) state that one of the purposes of IRT is to tie together "a number of threads from the organizational literature". The figure below summarizes these treads. Specifically, Daft and Lengel (1986) integrated equivocality with uncertainty and argued that structural characteristics which determine the amount and richness of the information processing are used to cope with these two communication-influencing factors. Figure 4 also stipulates the central importance of media richness fit to the medium used which is characteristic for the IRT and its further spinoffs.

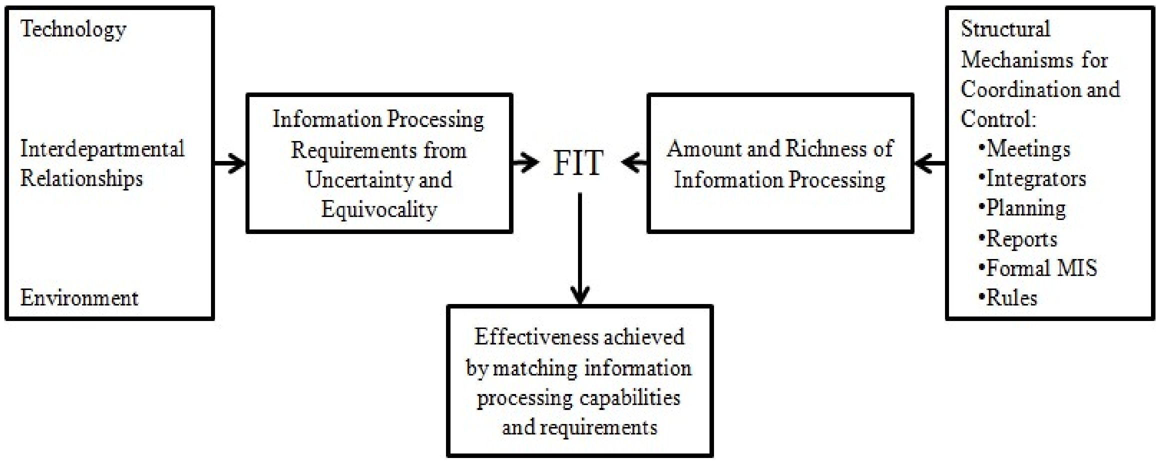


Figure 4: Information Richness Theory (Daft and Lengel 1986)

IRT has been used extensively in multiple academic disciplines to explain information and communication related phenomena. Lengel and Daft (1989) analyzed executive communication patterns using IRT. Their analysis show that a rich medium like face-to-face communication should be matched with non-routine, difficult-to-understand messages. A lean medium, such as the written memo, is best used for routine messages. Lengel and Daft further conclude that failure to make these matches often cause a misunderstanding. IRT can be used to measure appropriateness of media for different organizational communication activities (Rice 1993). Raman et al. (1993) uses similar theoretical lenses to study group decision support systems. According to their findings, groups using a communication medium that is too lean for their task seem to experience more difficulties than groups with a communication medium that is too rich for their task. Workman et al. (2003) used IRT to frame the investigation of teleworking and virtual teams. Their findings indicate that different cognitive styles and types of media contribute to the member commitment to virtual teams. For example, jobs that are more defined (i.e. administration) can be sustained with lean media, whereas more uncertain jobs (i.e. software development) seem to be better supported by the richer media channels. Simon and Peppas (2004) designed an empirical study to examine website visitors' preference when it comes to the richness of the presented information. Results of their study show that Internet users have more positive attitudes and higher levels of satisfaction with rich than lean sites, regardless of the complexity of the actual product they were looking for. Anandarajan et al. (2010) employ IRT to study the early Digital Natives and their adoption of instant messaging. Results of their field studies posit that the users will be more likely to believe a medium is useful for socialization if the said medium is information rich.

IRT is also widely used to investigate email correspondence. O'Kane and Hargie (2007) suggest that e-mail is affecting computer mediated and face-to-face communication in both positive and negative ways, producing intended and unintended outcomes. O'Kane and Hargie also argue that high volumes of email (i.e. information overload) handicap individuals' ability to answer them. Contrary to IRT predictions, individuals can understand email as being able to transmit more information than voicemail (El-Shinnawy and Markus 1997). These results fail to support IRT predictions, but they do support alternative explanations of people's media choice behavior. Although some users may perceive email as richer in information compared to voicemail, electronic mail richness perception varies across individuals (Schmitz and Fulk 1991). Choi and Toma (2014) also used IRT to ground their study on interpersonal media. In it they concluded that easily accessible and non-intrusive media (i.e. texting, Twitter) are more likely to be used for sharing positive than negative events. They also concluded that intrusive and rich media (i.e. phone calling) are more likely to be used for sharing negative than positive events.

From the standpoint of IRT, individuals are expected to select the mode of communication based on fine-tuning the equivocality of the message to the richness of the information channel. However, organizational communication practice tends to deviate from that standpoint. Those deviations are caused by organizational communication norms (Treviño et al. 2000), social presence (King and Xia 1997), social influence (Turner and Reinsch 2007) and relationships between individuals (Sheer and Chen 2004). Furthermore, Channel Expansion Theory (Carlson and Zmud 1994, 1999) posits that individual experiences can also create deviations. Carlson and Zmud (1994) classify those experiences in four categories: experience with the communication channel, experience with the messaging topic, experience with the organizational context and experience with communication co-participants. Another important upgrade to IRT comes in the form of communication concurrency (Valacich et al. 1993). Communication concurrency, defined as the supportive capacity of the environment, is used to introduce computer mediated information channels to the original concepts of IRT. Valacich et al. suggest that there is no "one best fit" between tasks and media, since the results of their study suggest that technology "fit" is more properly assessed at the sub-process level. In other words, to meaningfully examine and support communication, "future research aimed at evaluating media effectiveness should focus on fundamental communication processes embodied in the tasks themselves".

Although the list of augmentations and congruent theoretical additions to the IRT is extensive, only one major critique for IRT is established in the literature. The substance of that theory is not designed to augment or compliment IRT like the works I discussed in the previous paragraphs, but to provide a completely different way of treating information processing and communication. That competing theory is Information Naturalness Theory (INT). I will now discuss premises of INT and juxtapose it with IRT to create theoretical base for this dissertation.

Information Naturalness Theory

Information Naturalness Theory[4] (INT) presents a stark contrast to Information Richness Theory (IRT). Unlike IRT, the fundamentals of INT are positioned in Darwinian thinking (Kock 2002) and rooted deeply in neurophysiology and cognitive neuroscience. Its author (Kock 2004) argues that the problems arising from overloading individuals with vast amounts of digital and computer mediated information are not going away. He further posits that many flaws in the earlier "so-called rational choice theories" keep surfacing and that new theoretical fundamentals are needed to mitigate those gaps. Those fundamentals "should probe deeper" than any other behavioral or rational approach theory to find "the missing element of human nature" which defines human "biological communication apparatus". Since the biological mechanisms used to produce and process communication in humans are located in the human brain, Kock (2004) uses neurophysiological themes like "neural functional language system" (Lieberman 2002) and "brain circuits" to root his theory in the existing concepts from neuroscience.

[4] Information Naturalness theory is also known as Media naturalness theory and as Psychobiological model.

INT notes that human ancestors communicated primarily through face-to-face communication. Kock (2004) explains that this form of communication was so important to early humans that a set of harmful mutations survived multiple evolutionary cycles just so that humans could be more proficient in communicating in face-to-face manner. He highlights the example of vocal cord mutations. This mutation enabled humans to produce a wide variety of articulated sounds needed for face-to-face communication. However, the handicap of greatly increasing the possibility of choking while eating had to be endured. Without the risks of choking, it would be hard to make vocal cords mutations possible. After the modification in vocal cords, humans gradually developed brain structures which facilitate information processing common for face-to-face communication. As a result of these evolutionary pressures, Kock (2002, 2004) posits that the face-to-face communication is the most effective and also the most rewarding form. Specifically, he states that this way of communication is tied to pleasurable feelings inside the human brain. He also argues that other forms of communication create cognitive pressures and may lead to Information Overload in humans. The figure below (Kock 2004, p. 340) represents Kock's understanding of Information Naturalness.

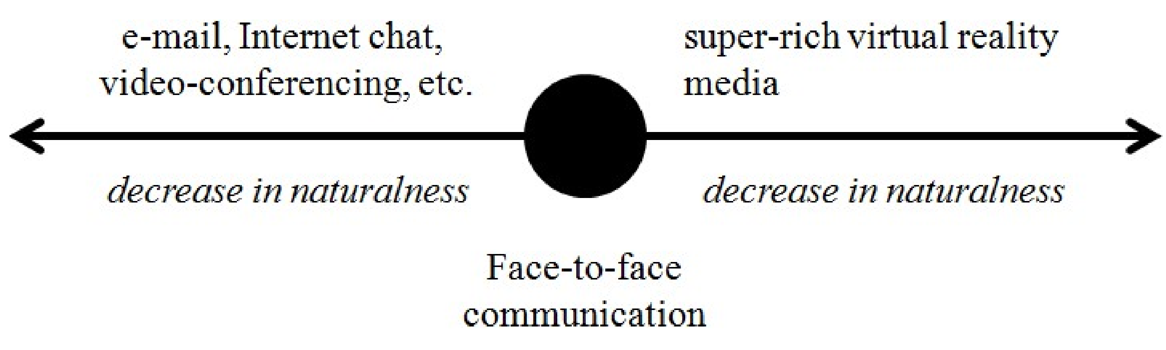


Figure 5: Information Naturalness Theory (Kock, 2004)

Although Kock explicitly states that all forms of communication which do not classify as face-to-face communication have a lower level of naturalness, he also argues that different ways in which the information is transmitted are not identical when it comes to their degree of naturalness. Figure 6 was developed on the basis of "Context-Specific Hypotheses Developed Based on the Psychobiological Model" from Kock's seminal work (2004, p. 338). It is used to represent varying levels of naturalness in different communication settings. It is important to note that IRT essentially uses the same logic to group the media; with minor concept-based exceptions (i.e. there were no video conferencing mechanisms at the time when the IRT was formulated).

One of the most unnatural forms of communication is email. Although widely used, emails are a very unnatural way of communicating for humans since the evolution of our brain has yet to catch up with this relatively recent technological development. Instant messaging is a more natural way of communicating because it eliminates asynchronous elements present in communicating via email. Audio conferencing presents a significantly more natural way of communicating since it uses parts of the brain and human anatomy which did have enough time to evolve to support efficient information processing. Finally, video conferencing is one of the most natural means of communicating because it closely resembles face-to-face communication. Thus, the more natural the communication channel is, the more efficient the communication would be. In his later work, Kock (2005) expands the definition of naturalness. In it, he assumes that natural communication involves five key elements: (1) high degree of co-location, (2) high degree of synchronicity, and the ability to convey and observe (3) facial expressions, (4) body language and (5) speech. Therefore, the naturalness of a medium can be assessed based on the degree to which the technology selectively incorporates (or suppresses) those five elements.

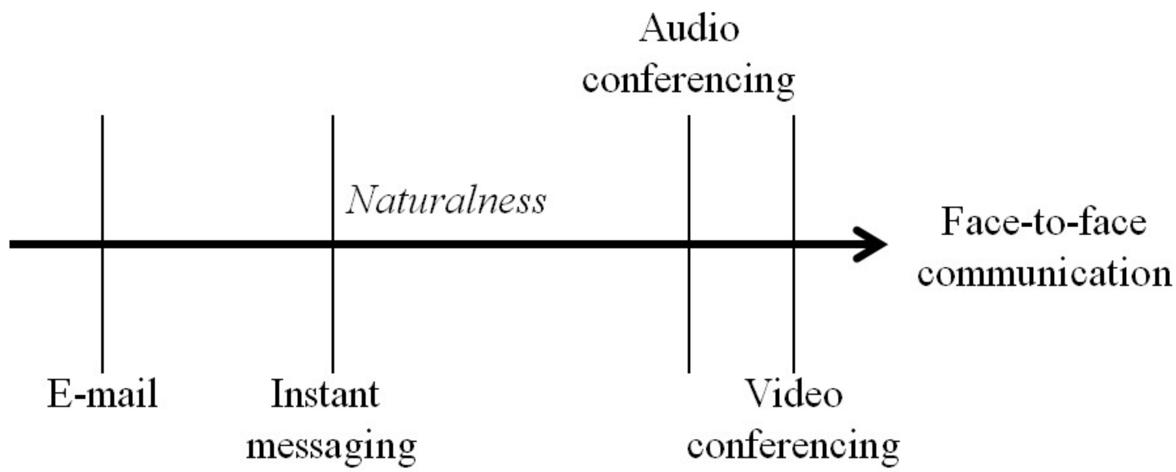


Figure 6: Varying levels of naturalness in different communication settings

Furthermore, INT links a set of dependent communication constructs to one central independent construct. This central construct is the mismatch between human neurophysiological communication apparatus and communication media characteristics. Kock (2005) states that “inverse of this mismatch is defined as the naturalness of a communication medium—that is, the higher the mismatch, the lower the naturalness of a communication medium.“ He links four sets of predictions to this mismatch.

The first set of predictions revolves around implications with cognitive effort, ambiguity of communication and arousal in physiological means. All things being equal, INT predicts that a decrease in the degree of naturalness will result in an increase in cognitive efforts, increase in communication ambiguity and in a decrease in arousal. A second set of predictions posit that digital communication will keep eliminating key elements of face-to-face communication to create other benefits. A third set of predictions argues that the level to which a digital communication medium supports an individual's ability to listen and convey speech is crucial in assessing naturalness. Finally, the fourth set of predictions focuses on compensatory adaptation. In it, Kock (2005) hypothesizes that individuals engaged in digital communication can change their behavior to overcome limitation of digital media.

In addition to relying on neurophysiological foundations, Kock (2004) also introduces the aspects of environment. INT treats cultural and social environments as a schema generating mechanisms. Individuals raised in different environments will develop different communication schemas. Different schemas ultimately lead to communication ambiguity, which can increase the probability of misinterpretations of particular communication elements.

Similar to IRT, INT was widely used in multiple disciplines and settings. Deluca (2003) uses it study business process improvements in asynchronous digital collaborations. Moreover, INT is also used to frame studies of virtual teams. For example, DeRosa et al. (2004) employ it to study solutions trust and leadership problems which are rooted explicitly in an evolutionary context. Similarly, an experimental study of credibility in e-negotiations (Citera et al. 2005) also takes the Darwinian approach used in Kock's INT. Moreover, research on maintenance of distributed relationships (McKinney and Whiteside 2006) uses INT to explore the possibilities of maintaining meaningful relationships between business partners in and after cases of an emergency (i.e. 9-11 terror attacks). Media naturalness also plays a major role in designing new frameworks to help prepare students for roles that involve negotiating, supporting, and facilitating virtual global collaboration (Paretti et al. 2007). INT has been used to explore the barriers to knowledge transfer through the means of computer-mediated communication (Schwartz 2007). Kock et al. (2007) similarly utilizes INT to investigate how media obstacles can be compensated in digital communication. This research demonstrates that the burden of compensating for electronic communication media obstacles falls primarily on those who attempt to convey information, as opposed to those who receive it. Moreover, media naturalness builds the base for understanding how gestures for online virtual environment interactions work (Verhulsdonck 2007). Hrastinski (2008) uses the synchonicity aspect of INT to study how potential problems of trust and leadership in virtual teams are affected by synchronous communication. Peng and Sutanto (2012) relied on INT to study knowledge sharing across functional and geographical boundaries. Media naturalness was also used in studies about deciding whether to accept or reject contract clauses in software purchasing contracts (Kock et al. 2015).

Theory Review Summary

Seminal information theories like Information Richness Theory (IRT) and Information Naturalness Theory (INT) are useful in providing a holistic picture of the communication and related information processing phenomena. I use this picture to ground this dissertation in those two theories. Table 5 provides a concise overview of IRT and INT and their major components. A central premise in IRT is that different communication media have different abilities to transfer information. This ability is defined as Information Richness. INT posits that the human brain did not yet evolve to process unnatural communications effectively. Thus, the more communication medium differs from the face-to-face communication, the greater the cognitive effort will be required to communicate. In terms of Information Overload (IO), IRT posits that IO may come not only from the sheer amount of available information but also from the mismatch between Information Richness and task complexity.

For example, a short message might be more suited for arranging a meeting than a lengthy 4k video. INT argues that unnatural communication will require more cognitive effort. Thus, other things being equal, less natural media (i.e. email or asynchronous message) will create more cognitive pressures for the individual compared to a more natural media (i.e. voice conference) even in the case of IO. Both IRT and INT incorporate communicational disturbances which can also play a role in understanding how IO might manifest. Specifically, IRT lists different organizational norms, skill sets and culture as potential culprits for reducing the communication effectiveness. It follows that the effects of IO can be further amplified if the sources of information influx are misaligned with the receiver's characteristics.

INT highlights cognitive schemas as potential disruptors of effective communication. Thus, if information influx is coming from a source which uses radically different cognitive schema compared to the schema which is used by the receiver, IO effects can be reasonably expected to amplify as well. In short, both IRT and INT explain the same phenomena (communication) by analyzing the core media of the said phenomena (information) from radically different perspectives. Taken together, these theories provide a solid ground for researching IO. The following sub-chapter will use that theoretical ground to build a theoretical mechanism for understanding IO through the CNDs and to explicate a set of hypothesis relating to it.

Table 5: IRT and INT components

Component	IRT	INT
Level of analysis	Started at organizational; used at organizational and individual levels.	Individual level.
Central premise	Communication media vary in ability to enable users to communicate and to change understanding. The degree of this ability is known as a medium's "richness."	Human ancestors have communicated primarily in face-to-face mode. Evolutionary pressures have led to the development of a brain that is consequently designed for that form of communication.
Core concept	Information richness should fit the communication task.	The most natural way for humans to communicate is face-to-face.
Media selection	Richer media for complex tasks, lean media for simpler.	The more natural the media is, the less cognitive efforts will be needed to communicate.
Core characteristics/ constructs	Speed of feedback, cue multiplicity, language variety, personalization	Cognitive effort, communication ambiguity, and physiological arousal
Communication disturbances	Different skill sets, norms and cultures.	Different cognitive schemas.
Key difference	Richness is not uniformly better. Fit between communication task and the medium used is central.	Naturalness is always better – the more naturalness the lower the cognitive efforts will be.
Theoretical spin- offs	Channel expansion theory Communication concurrency theory	/

Theoretical Mechanism of Information Overload

In this sub-chapter, I present the Theoretical Mechanism of Information Overload and the corresponding hypotheses. The mechanism and the hypotheses are based on the literature presented in the earlier parts of this chapter. Both the mechanism and the hypotheses are designed to further the existing theoretical and literature discussion and to build on the detected gaps and shortcomings I explain in previous parts of this chapter. I am using Gregor's (2006) understanding of the nature of theory in IS to develop Theoretical Mechanism of Information Overload. Thus, I hold that an IS theory should have the following structural components: means of representation, constructs, statements of relationship and scope. This sub-chapter also serves as an introduction to all structural elements and relationships of Theoretical Mechanism of Information Overload and the corresponding hypotheses. Hypotheses 1a, 1b, 1c and 1d deal with elementary cognitive performances (ECT) and Information Overload (IO). This group of hypotheses tests if IO influences ECTs in a stronger way, how the growing amount of information influences ECTs and how derivates of cognitive schemas (Kock 2004) separate two distinct population groups. Hypotheses 2a and 2b put Information Richness and Information Naturalness Theories (IRT and INT respectively) to the test. In other words, hypotheses 2a and 2b are designed to examine if IO is negatively related to the Information Richness and Information Naturalness. Finally, the third hypotheses includes and extends a specific Consumer Neural Devices (CND) study (Milic 2017) and sets the scene for testing how the same CND can be used to research IO phenomena in real-time and outside of the standard clinical settings. Combined, these hypotheses form a theoretical mechanism of understanding how the state of growing available information influences cognitive performances through the state of Information Overload and how different cognitive schemes, Information Richness and naturalness shape the entire IO mechanism.

Previous parts of this chapter provided a base for understanding how the general literature from the business disciplines understands IO. Although the situations in which some forms of IO occur are systematically listed throughout the literature (i.e. Eppler and Mengis 2004), an overarching understanding of the causal and cognitive mechanisms behind the IO is still missing. This is particularly clear in situations when different disciplines approach IO from multiple levels. For example, marketing studies are known to analyze IO just from the consumer's perspective while accounting studies take auditor's perspective as central. Similarly, managerial studies focus on executive and organizational narratives.

Despite this diversity of topics and disciplines, two key IO elements are present in multiple literature themes and studies. These key elements are:

1) state of abundant information and

2) constant and growing flow of information.

The IO definition proposed by Speier et al. (1999) directly encompasses the first element by understanding it as a state in which individuals have a vast amount of information that is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation. This state is indirectly present in multiple studies. For example, Berghel (1997) elaborates about the state of abundant information which occurs during internet browsing. Bawden (2001) advocates that information excess occurs when individuals screen medical information. Moreover, Meyer (1998) discusses that too much information is also characteristic for strategic analysis and planning. Excesses of information are also known to manifest during meetings and telephone conversations (Schick et al. 1990), ideation processes (Grise and Gallupe 1999), face-to-face discussions (Sparrow 1999), product evaluations (Herbig and Kramer 1994) and even in regular shopping activities in supermarkets (Jacoby 1984). Thus, it can be concluded that individuals frequently experience situations in which they have a vast amount of information at their disposal. Similarly, individuals can frequently end up in a situation where they have a volume of readily available information and in scenarios with no mechanisms to mitigate the risk of misinformation. Thus, this dissertation uses the state of abundant information and labels it as Information Excess. I position Information Excess as one of the key constructs of my theoretical mechanism and a constituent element of IO. The conceptual definition of Information Excess is provided in this chapter and explicated in Table 6.

The second key element of IO is the constantly growing amount of information. I define this growing amount of information as information influx. Regardless of the research setting or level of analysis, literature again paints a picture similar to the one I found for the first key element: multiple papers discuss the constantly growing amount of information in different ways and in multiple scenarios. For example, Chewning and Harrell (1990) argue that growing amount of information eventually results in a state where the available information is utilized to a lesser degree. They, as well as some other authors (i.e. Cook 1993; Griffeth et al. 1988; Schroder and etc 1967; Swain and Haka 2000), argue that this relationship takes a inverted U-curve shape (Eppler and Mengis 2004). Other authors (i.e. Jacoby 1984; Malhotra 1982; Meyer 1998) claim that information influx pushes individuals into the state of Information Overload only when the amount of information exceeds the processing capacity of the human brain. Keller and Staelin (1987) contribute to the literature by introducing a temporal aspect to the information influx. They posit that the state of Information Overload will occur when the available time to process the given task becomes greater than the time in which the new amount of information arrives. Some authors (i.e. Wurman 2000) take even higher perspective by claiming that information influx creates the state of Information Overload when the amount of "ingested" information exceeds the resources available for "digesting" information. Thus, it can be concluded that information influx is indeed present throughout the literature in both direct and indirect manners. Consequently, I stipulate that information influx occurs when an entity, be it an individual, website visitor, IS auditor, consumer or a manager, faces a situation in which the flow of information is constant and the amount of information is growing. This dissertation defines the state of constant information flow and growing amount of information as Information Influx. Information Influx plays the role of the second construct in my theoretical mechanism.

The second part of NeuroIS sub-chapter provided grounds to include cognitive functions of the human brain into the study of IO. Those grounds are functional, anatomical and contextual. When it comes to the function of the brain, the executive part of the brain positioned in the frontal lobe processes higher cognitive efforts. This same area is known to be active when the brain uses the executive center (i.e. PFC) to process information and support activities like cognition and working memory. This creates the anatomical grounds for linking IO to elementary cognitive tasks. Finally, all NeuroIS studies in which causes and situations of IO might have occurred have used cognitive perspectives. Thus, this dissertation uses a concept of elementary cognitive tasks (ETC) as both a conceptual and methodological measure of an individual's cognitive performances. I use a commonly accepted definition of elementary cognitive task (ETC) from Carroll (1993, p. 11) in which he defines ETCs in the following way:

> *"An elementary cognitive task (ECT) is any one of a possibly very large number of tasks in which a person undertakes, or is assigned, a performance for which there is a specifiable class of "successful" or "correct" outcomes or end states which are to be attained through a relatively small number of mental processes or operations, and whose successful outcomes depend on the instructions given to, or the sets or plans adopted by, the person."*

In other words, ECTs can be understood as basic tasks with which demand only a small set of mental processes and which have easily specified correct outcomes. To an extent, these tasks are congruent with mid-level tasks like report and planning specified in the second figure of Daft and Lengel's (1986) information role structural framework (p. 561). This theoretical congruency renders the concept of ECT particularly useful for the role of the third construct in the IO mechanism.

Theory literature review sub-chapter states the main characteristics of IRT and INT. Both theories have well developed definitions of Information Richness and Information Naturalness respectively. I adopt those definitions verbatim and use them as constructs in my IO theoretical mechanism. Therefore, the ability of a communication medium to reproduce the information sent over it is understood as Information Richness, while the level to which the communication medium is similar to human face-to-face communication is understood as Information Naturalness. Table 6 provides a concise list of all five constructs I use to explain the mechanism behind IO.

According to Gregor's (2006) Structural Components of Theory (p. 620) a well developed IS theory should also have a clearly specified scope. Gregor (2006) defines theoretical scope as "the degree of generality of the statements of relationships" (p. 620). As stated in introductory chapter, the scope of this dissertation, and thus of my theoretical mechanism focuses completely on the individual level and on digital representations of information. Therefore, this theoretical mechanism is meant to explain the workings of Information Overload on individual scope. The next part in formalizing my theoretical mechanism includes explicating the relationships between the constructs. Taken together, the constructs presented in Table 6 are characteristic of most, if not all, IO situations.

Thus, I believe that the first attempt at theorizing an overarching mechanism for understanding how IO manifests itself should incorporate all these constructs. Introductory parts of Chapter Two of this dissertation provide examples on how those constructs apply in specific situations. However, these situations alone do not provide an understanding of relationships among the core IO constructs. In particular, it is clear that information influx causes the state of IO.

However, it is not clear if information influx causes a stronger effect on ECTs on its own or if stronger effects come only after the state IO is reached. Furthermore, an indirect and partial consensus on Information Richness influencing IO negatively exists throughout the literature. Unfortunately, this relationship has not been empirically tested. Thus, it is certain that that these stances play an important but not fully understood role in the IO mechanism. As such, I believe they should be tested and potentially included as statements of relationship (i.e. constituent forces) of the IO theoretical mechanism.

Table 6: Key Constructs for IO Mechanism

Key constructs	Definition
Information Excess	A state in which individuals have vast amount of information that is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation. This is the second key element of Information Overload.
Information Influx	The state of constant information flow followed with the growing amount of information. This is the second key element of Information Overload.
Cognitive performances (ECT)	Basic tasks which demand only a small set of mental processes and which have easily specified correct outcomes.
Information Richness	The ability of communication medium to reproduce the information sent over it.
Information Naturalness	The level to which the communication medium is similar to human face-to-face communication.

When it comes to INT, a clear agreement exists: the more natural the information is, the lesser the amount of cognitive effort is exerted by the individuals consuming said information. Similarly to IRT, this consensus is not empirically tested – especially not with the experimental design which employs any form of neural equipment and explains the causal mechanisms behind the information overload. Paradoxically, although multiple works seems to be in line with Kock's (2002, 2004) reasoning that evolutionary pressures have shaped the human brain, not a single study has tested these conclusions by employing actual measures from the human brain or any causal mechanisms whatsoever. Thus, a case for testing if these theorized relationships hold exists. In terms of this

Theoretical Mechanism of Information Overload, the case for testing is particularly strong for exploring if Information Richness and Information Naturalness relate to the levels of IO overload directly and negatively. Additionally, IRT introduces the concept of information fitness (i.e. short texts for scheduling meetings, face-to-face meetings for complex tasks) which might also influence the IO mechanisms. However, information fit is not tested in this dissertation since CNDs at their current level of development simply do not have the technical capabilities to reliably detect the neural constructs required to conduct such a study. Combined together, these gaps and key concepts provide a comprehensive ground for theorizing the relationships behind the core constructs of IO mechanism. Conveniently, this mechanism should be testable using CNDs, since the dependant variable (ECT) can be mapped with minimal dimension reductions to the neural correlates detectable by almost all CNDs. I use table below to list all statements of relationships present in the Theoretical Mechanism of Information Overload. Gregor (2006) also argues that IS theory is to be accompanied by the adequate means of representations. She specifies that a good IS theory should be "physically represented in different ways: in words, mathematical terms, symbolic logic, diagrams, tables or graphically" (p. 620).

Table 7: Relationships between Constructs of the Information Overload Mechanism

Rel. #	Statement of Relationships: Description
1	Stronger ECT effects are caused by Information Overload. However, information influx and information excess alone cannot create strong ECT effects.
2	Stronger ECT effects are present even after the intensity of information influx returns to normal levels.
3	Digital Natives are environmentally conditioned to process digital information more effectively than Digital Migrants. Therefore, Information Overload will create smaller ECT effects on Digital Natives compared to Digital Migrants.
4	Digital Migrants are not environmentally conditioned to process digital information more effectively than Digital Natives. Therefore, Information Overload will create greater ECT effects on Digital Migrants compared to Digital Natives.
5	Information richness reduces the cognitive efforts required for the human brain to process information. Thus, Information Richness reduces the strength of ECT effects of Information overload.
6	Information naturalness reduces the cognitive efforts required for the human brain to process information. Thus, Information Naturalness reduces the strength of ECT effects of information overload.

To satisfy this requirement, I use a graphical representation of the IO mechanism provided below (Figure 7) to accompany the means of representations (i.e. words and tables) I discussed earlier in this subchapter. Horizontal axis of Figure 7 defines the temporal dimension, while the vertical axis stands for the strength of ECT effects.

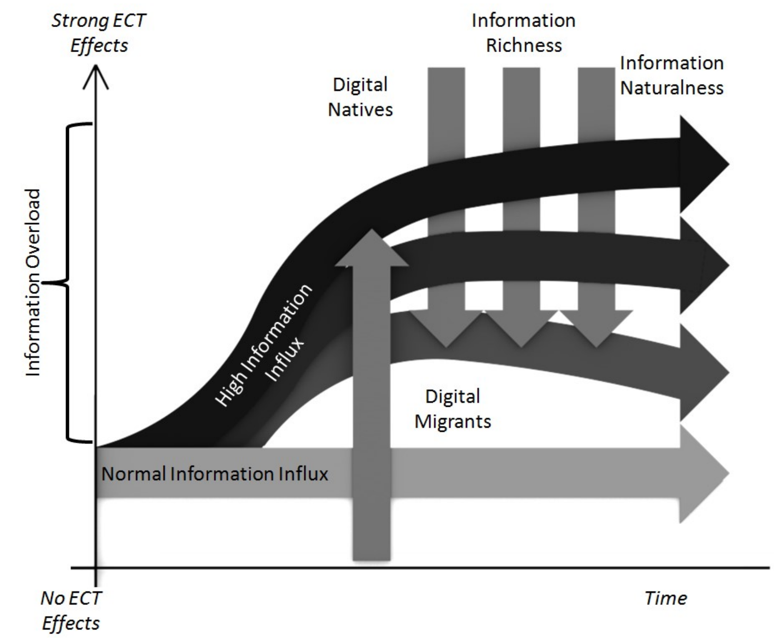


Figure 7: Information Overload Mechanism

The straight light-gradient vertical arrow named "Normal Information Influx" represents the state in which individuals are exposed to standard (i.e. non-overloading) levels of information influx. This element of the mechanism serves as an orienteer for explanation and representation of causal relationships between key IO constructs and individual ECTs performances over time.

The three curved dark-gradient arrows labeled "High Information Influx" represent the changes in information influx intensity. These changes occur under different key IO constructs, which transform the normal information influx into the states of high information influx, and ultimately create IO. To begin with, Kock (2004) claims that the environment in which an individual is located can influence the individual's ability to process information. On that basis, I theorize that IO in Digital Natives will have smaller ECT effects, since Digital Natives are brought up in an information-abundant environment and thus already partially conditioned to high information influxes and information excess. On the same basis, I theorize that the opposite relationship will hold in cases of Digital Migrants, especially since the environment in which they grew in were not as information-abundant as the one characteristic for Digital Natives. This part of the mechanism is represented graphically by the first two vertical arrows. The first vertical arrow shows how the membership in the Digital Migrants group amplifies the ECT effects coming from the high information influx. The amplified high information influx is represented by the curved arrow with the darkest gradient. The curvature of the arrow/s represents the change in the intensity of information influx, since I posit that every information influx starts as a normal information influx. The opposite relational logic holds for Digital Natives: the membership in the Digital Natives group weakens the ECT effects coming from the information overload. The weakened High information influx is represented by the curved arrow with the lightest gradient.

The third and the fourth vertical arrows represent the part of the mechanism through which explanation of how Information Richness and Information Naturalness affect Information Overload is illustrated. Both Daft and Lengel (1986) and Kock (2002, 2004) argue that the Information Richness and Information Naturalness respectively improve the efficiency of communication especially within the scenarios that are of interest to the IS discipline. In other words, both IRT and INT understand Information Richness and Information Naturalness as characteristics which exert positive influence on communication efficiency. And since Information Richness and Information Naturalness increase the communication efficiency, I posit that this increase in communication efficiency creates a lower cognitive load on the parts of the brain processing these signals. Therefore, I theorize that the richer and the more natural the information is, the smaller the effects of ECTs will be.

To summarize, my theoretical mechanism posits that Information Overload will manifest and create strong effects on ECTs only when both key elements of IO (i.e. information influx and information excess) are present. Normal information influx alone cannot cause significant effects on ECTs. Same holds for information excess: without the information influx individuals will eventually process or verify the available information and strong effects on ECT performances will be avoided. I also posit that this theoretical mechanism will not work universally for every type of information and for every age group. In particular, I theorize that richer and more natural information will weaken the strength of ECT effects of IO. Similarly, I also theorize that Digital Natives will experience smaller ECT effects compared to Digital Migrants. I ground this part of the mechanism on the environmental factors presented in INT (Kock, 2004). In short, this theoretical mechanism defines what Information Overload is on the individual level. The same theoretical mechanism also explains how and when information influx and information excess create stronger elementary cognitive task effects. Moreover, this mechanism explains why Information Overload results in stronger elementary cognitive task effects. Finally, Theoretical Mechanism of Information Overload provides basis on which it is possible to predict when stronger effects on elementary cognitive performances will occur. Thus, I believe that the theoretical mechanism I present here can be classified as the Type IV theory, or as an Explanation and Prediction theory in Gregor's (2006) Taxonomy of Theory Types in Information Systems Research (p.620).

In the remainder of this sub-chapter I provide a set of hypotheses, designed to test if the mechanism I just theorized is supported with the data coming from the CND.

Hypotheses Group One: Cognitive Performance and Information Overload

Hypotheses from the Group One are designed to test if the first four relationships (Table 7) of the Theoretical Mechanism of Information Overload work in empirical settings and in measurable ways. I present these hypotheses in the table bellow (Table 8). Hypotheses 1a and 1b test if strong ECT effects are caused by high information influx and the state of information overload. These two hypotheses are developed on the basis of the literature from earlier parts of this chapter, which concludes that IO influences user performances in different ways. As I discussed earlier, Chewning and Harrell (1990) argue that growing amount of information eventually results in a lesser use of information. Other works (i.e. Cook 1993; Griffeth et al. 1988; Schroder and etc 1967; Swain and Haka 2000) claim that this relationship is represented by a U-curved shape (Eppler and Mengis 2004). Another group of authors (i.e. Jacoby 1984; Malhotra 1982; Meyer 1998) relate Information Overload to the processing capacity of the human brain.

Keller and Staelin (1987) introduce a temporal aspect to the information influx by arguing that that the state of IO happens when information arrives faster than it can be processed. On this basis I concluded that information influx occurs when an individual faces a situation in which the flow of information is constant and the volume of information is increasing.

Table 8: Hypotheses Group One and the corresponding Statements of Relationships

H.#	Text	Rel. #
H1a	Information Overload leads to strong Elementary Cognitive Task effects.	1
H1b	Information Influx does not lead to strong Elementary Cognitive Task effects Information Overload is reached	
H1c	Information Overload caused Elementary Cognitive Task effects endure even after the information influx is stopped	2
H1d	Information Overload leads to stronger Elementary Cognitive Task effects on Digital Natives compared to Digital Migrants.	3 & 4

Therefore, Information Overload should result in stronger effects on basic tasks which demand only a small set of mental processes and which have easily specified correct outcomes. However, these effects will not occur unless information influx is accompanied by the information excess (i.e. Table 7, statements of relationships number 1). Stated formally:

H1a: Information Overload leads to strong Elementary Cognitive Task effects.
H1b: Information Influx does not lead to strong Elementary Cognitive Task effects Information Overload is reached

A seminal IO literature review (Eppler and Mengis 2004), as well as the literature review I have conducted, concur that IO can happen in multiple situations. However, to the best of my knowledge, all IO literature seems to focus on investigating situations, relations, effects and potential countermeasures in relation to IO. I theorized earlier that strong ECT effects should be present even after the intensity of information influx returns to normal levels (i.e. Table 7, statements of relationships number 2). However, not a single study focuses on researching if IO influences cognitive performances after the high information influx, returns to the normal levels. And since a range of IO countermeasures have been developed, it can be assumed that IO does influence cognitive performance even after the information influx returns to normal values. I believe that this property of the IO mechanism can extend the understanding of this phenomenon and expand the dialogue from the literature. Therefore, I propose Hypothesis 1c:

> *H1c: Information Overload caused Elementary Cognitive Task effects endure even after the information influx is stopped.*

.

The figure below illustrates the part of the Theoretical Mechanism of Information Overload that is tested through the hypotheses H1a, H1b and H1c. Understanding of Theoretical mechanism of IO would be incomplete without incorporating the effects coming from individual's membership in one of two distinctly different groups, with these groups being Digital Natives and Digital Migrants. As I theorized earlier (i.e. Table 7, statements of relationships number 3 and 4), Digital Natives are environmentally conditioned to process digital information more effectively than Digital Migrants.

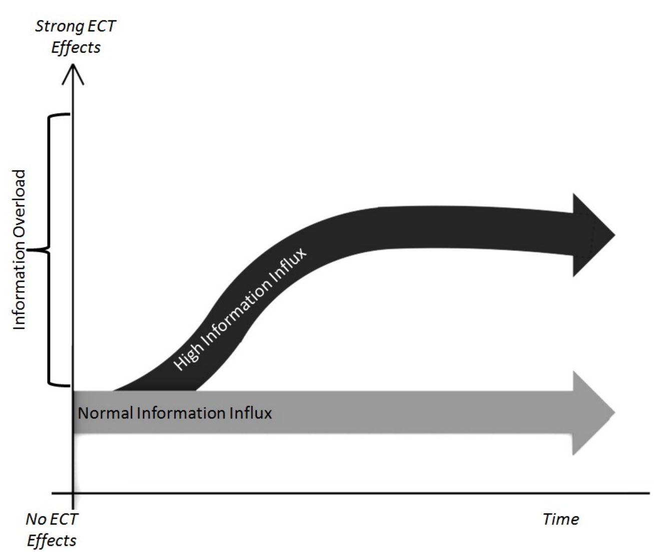


Figure 8: The basic Information Overload effects

Therefore, Information Overload is theorized to create smaller ECT effects on Digital Natives compared to Digital Migrants. Similarly, Digital Migrants are not environmentally conditioned to process digital information more effectively than Digital Natives. Therefore, Information Overload should create greater ECT effects on Digital Migrants compared to Digital Natives. As I discussed earlier, both IRT and IRT are univocal about the directionality and nature of these effects. Namely, IRT states that different cultural and departmental norms can distort the process of communicating information between individuals. INT posits that individuals raised in different environments tend to develop different communication schemas. Based on those positions, I hold that no two individuals would experience an influx of information in the same way. Therefore, these distinctly separate groups might end up experiencing IO to different extents. As I elaborate earlier, the classification which appears to be the most suitable for applying in the context of digitally transmitted information is the one which separates the general population into Digital Natives and Digital Migrants (Prensky 2001). On the one hand, Digital Natives can be defined as all individuals born or raised during the era of widely available digital technology (1980s and later). On the other, Digital Migrants are defined as all individuals born or raised during the times when digital technology was not as widely available or even available at all. Thus, it is reasonable to assume that Digital Natives have developed different cultural norms and cognitive schemas compared to Digital Migrants. Similarly, individual experiences (Carlson and Zmud 1999) between those two groups can be expected to differ significantly, which should further translate into differences in cognitive performance in digital environments between those two groups. Intriguingly, cognitive neuroscience does not provide a univocal position on this topic. In particular, it seems that cognitive performances deteriorate with age (Glisky 2007), which could mean that Digital Migrants might be more seriously affected by IO than Digital Natives, especially since their cognitive abilities are deteriorating as a result of aging. Since the difference between Information Overload effects on Digital Natives and Digital Migrants plays a crucial role in the functioning of the Theoretical Mechanism of Information Overload (i.e. Table 7, statements of relationship number 3 and 4), I hold that this part of the mechanism should be tested. Presented formally:

> *H1d: Information Overload leads to stronger Elementary Cognitive Task effects on Digital Migrants compared to Digital Natives.*

Figure 8 illustrates the part of the Theoretical Mechanism of Information Overload that H1d is set to test.

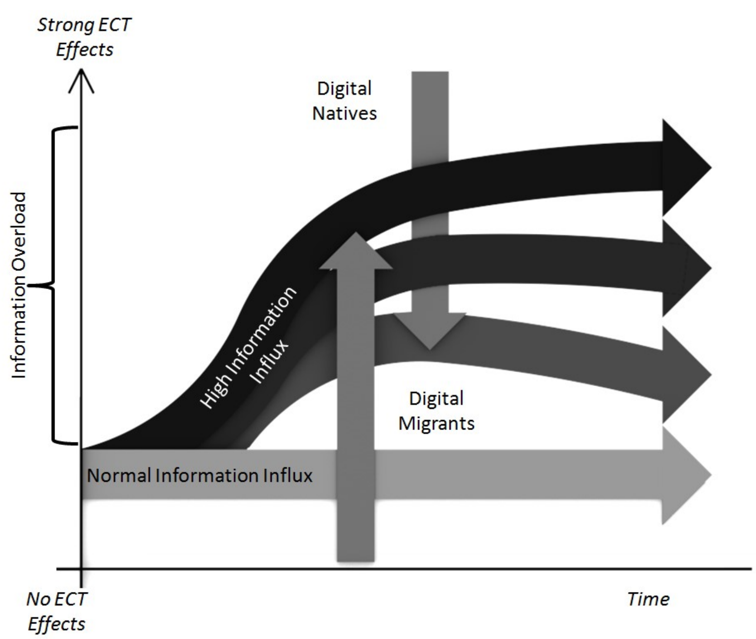


Figure 9: Information Overload - Digital Natives vs. Digital Migrants

Hypothesis 1d marks the end of the first group of hypotheses. The next group of hypotheses explicates postulates from IRT and INT and relates them to IO, as I previously theorized.

Hypotheses Group Two: Information Overload and Information Categories

As I theorized earlier, Information Richness reduces the cognitive efforts required for the human brain to process information. This further means that Information Richness, assuming task fit, reduces the strength of ECT effects of Information Overload. Theoretical Mechanism of IO contains an identical relationship for Information Naturalness. Namely, I theorize that Information Naturalness reduces the cognitive efforts required for the human brain to process information. Therefore, Information Naturalness should reduce the strength of ECT effects of Information Overload. These relations also play a vital role in the Theoretical Mechanism of Information Overload. As such, they are explicated in Table 7 as statements of relationships number 5 and 6 respectively. As I discussed earlier, both IRT and IRT are univocal about these effects. To formally test these elements of the theoretical mechanism I propose the following hypothesis:

> *H2a: Information Overload is negatively related to the Information Richness of the information category*

Figure 10 represents the part of the theoretical mechanism that is formally tested by H2a.

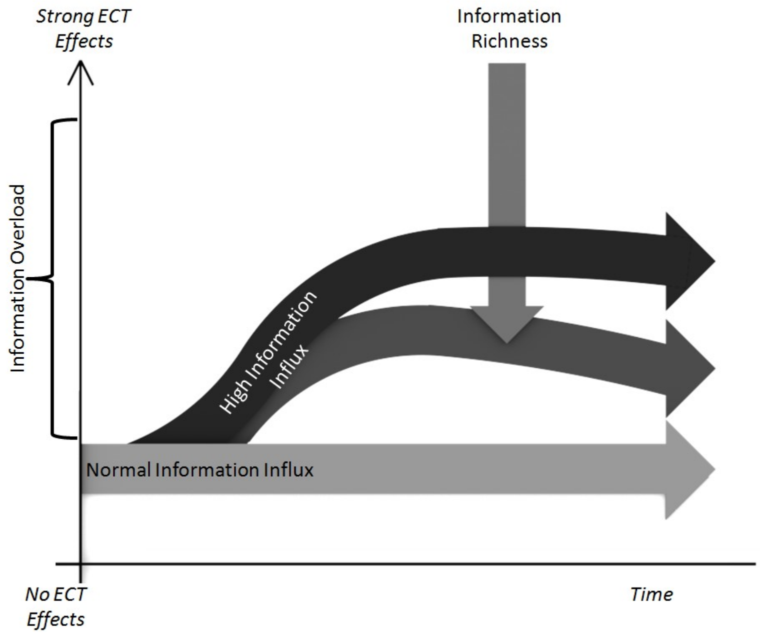


Figure 10: Information Richness effects on Information Overload

When it comes to the INT theory, the situation is much simpler. The more closely the communication resembles face-to-face communication, the less cognitive effort will be required to process the information. I incorporate this logic in the Theoretical Mechanism of Information Overload by stating that Information Naturalness reduces the ECT effects of Information Overload because Information Naturalness reduces the cognitive efforts required for the human brain to process information (i.e. statement of relationships number 6, Table 7). Hypothesis 2b, which is formally stated below is designed to test if this particular element of the mechanism is supported by data:

H2b: Information overload is negatively related with the media naturalness of the information category

Figure 10 illustrates the part of the theoretical mechanism that is formally tested by H2b.

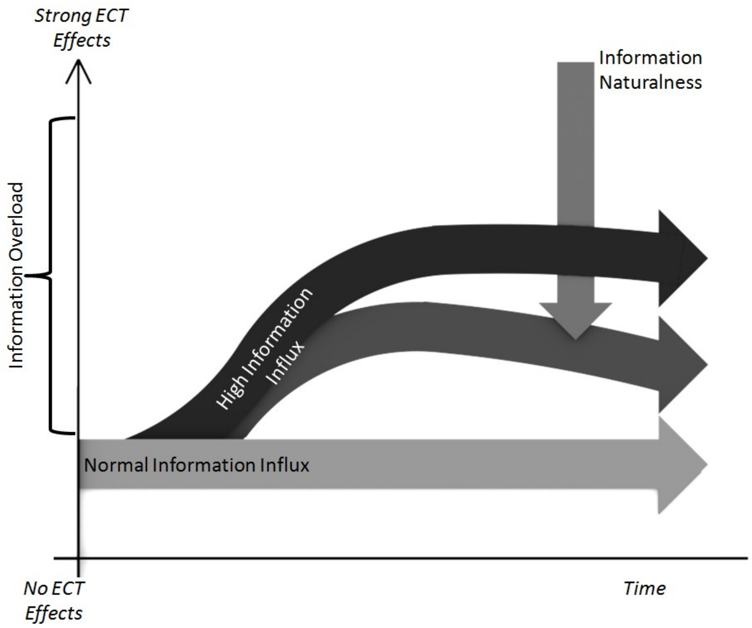


Figure 11: Information Naturalness effects on Information Overload

Hypotheses 3: CND IO Detection Potential

Hypotheses groups one and two are designed to test if the theoreticized mechanism of IO works in practice. However, another important component of this dissertation relies on detecting and understanding IO in real-time and by non-clinical devices. To ground Hypotheses 3, I present in verbatim the paper I have already published at the last Gmunden NeuroIS retreat (Milic 2017). In it, I explain how CNDs can be positioned within the existing NeuroIS toolbox and what procedures can be used to gather EEG signals. This preliminary paper has been published in a peer-reviewed Springer outlet and it can serve as a prelude to Hypotheses 3 and Chapter Three.

This research understands a Consumer Neural Device (CND) as a sum of hardware and software elements of a communications system that permits cerebral activity to control computers or external devices (Kübler et al. 2001; Lotte et al. 2007;

Nicolas-Alonso and Gomez-Gil 2012). CNDs can be grouped into two categories based on the invasiveness of the interface: instruments which are invasive and those which are noninvasive. Invasive interfaces require a medical procedure in which a physical part of a brain-to-computer interface is surgically inserted into a human brain (Engber 2016). Noninvasive CNDs stay outside of the human body – mostly in form of an easy-to-use headband. At the current level of technological development, CNDs are exclusively noninvasive. Main goal of this research is to position CNDs among other commonly used NeuroIS tools and to test the technical capabilities of a specific CND in a pilot study. This research proceeds as follows: a brief overview of thematic, methodological and theoretical advances in NeuroIS field is provided; followed by a two dimensional comparison of CNDs with widely used NeuroIS tools and with a set of available consumer grade brain to computer interfaces. Finally, this research concludes with a pilot study of a consumer grade CNDs and with a suggestion for future CND research topics.

In recent years, the Information Systems (IS) discipline started to embrace neural instruments and methods with the intention to complement existing topics and expand understanding of the emergent phenomena. This led to the creation of a specific branch of IS research, known as Neuro – Information Systems (NeuroIS). NeuroIS improved the capacity of IS research significantly and a number of research breakthroughs occurred as a result. NeuroIS has been recently used to answer multiple questions, ranging from better understanding of technostress (Tams et al. 2014), information processing biases in virtual teams (Minas et al. 2014b), understanding effects of emotional states on financial trading decisions (Astor et al. 2013), using measures of risk perception to predict information security behavior (Vance et al. 2014) and complementing business process modeling tools (Shitkova et al. 2014) to name a few.

Thus, it is not surprising that IS scholars started to lay theoretical and methodological grounds on which future research can be built. Reflections on the Gmunden Retreat from 2009 (Riedl, R. Banker, et al. 2010) re-defined what NeuroIS is, which tools are relevant for NeuroIS, what IS can learn from neuroscience and what were the current challenges for NeuroIS at that time. A research commentary (Dimoka, Pavlou, et al. 2010) illustrated the potential of cognitive neuroscience for IS research, especially when it comes to localizing the neural correlates of IS constructs, capturing hidden mental processes and challenging assumptions and enhancing IS theories. Vom Brocke and Liang (vom Brocke and Liang 2014) also contributed to the discipline with a set of guidelines for NeuroIS studies. Those guidelines are designed to help researchers to better understand phases typical for NeuroIS research and to guide NeuroIS research through the emerging standards of the discipline. Tams et al. (2014) used a technostress study to illustrate the holistic effects that come from using neurosciences and self reported data in tandem. Tams et al. improved our understanding on triangulating different sources of data by showing the scenario in which different measures can constitute as alternative and/or complements in the prediction of theoretically-related outcomes. Specifically, Tams et al. demonstrated that physiological and psychological measures can actually lead to divergent findings. Furthermore, Gregor et al. (2014) developed a nomological network with an overarching view of relationships among emotions and common constructs of interest in NeuroIS research. Finally, Müller-Putz et al. (2016) ventured deeply into the foundations, measurements and application of electroencephalography in IS. By publishing their work, Müller-Putz et al. equipped prospective NeuroIS researchers with solid methodological foundations for conducting EEG based research.

Although NeuroIS continues to prove its value by expanding the knowledge on multiple IS related phenomena; and although sound theoretical and methodological foundations of NeuroIS have been laid out, many IS researchers can still feel reluctant to venture into NeuroIS topics. Some are turned away by significant resources required to conduct a NeuroIS study (Dimoka 2012), while others are discouraged by the sheer breadth of non – IS knowledge required to successfully conduct a state of the art NeuroIS experiment (Müller-Putz et al. 2015a). For example, NeuroIS research requires researchers to select a proper instrument and equipment that will adequately detect all elicited aspects of researched phenomena, create and maintain all required parameters for the instrument to operate optimally and finally to analyze the readings from the clinical grade neural interfaces (vom Brocke and Liang 2014; Müller-Putz et al. 2015a; Tams et al. 2014). Few IS researchers are properly trained to conduct those studies and some can be deterred by administrative hurdles required to conduct medical-grade research on human subjects. All those factors combined prevent NeuroIS from becoming one of the dominant areas of IS research.

Additionally, preconceived notion of complexity, ambiguity and dangers (Engber 2016; Piore 2015) of neural instruments may also be one of the culprits for relatively low proliferation of neural technologies outside the academia. Specifically, it has been known for four decades that the human brain can communicate directly to computers via brain to computer interfaces (Kübler et al. 2001), yet proliferation of those interfaces never happened. Companies like Emotiv, Neurosky and Microsoft are known to work on CNDs (Riedl, R. Banker, et al. 2010) and multiple CNDs are even available to a wide consumer audience – but to no avail. Organizations and individual users are still reluctant to include CNDs into their IS infrastructure.

That situation on the ground can perplex IS researchers: Why is it so that despite a growing research momentum, wide use of CND did not happen? This research posits that a wide proliferation of CNDs did not happen because the consumer side of NeuroIS is still largely unexplored. In order to explain our reasoning, an overview of the most common NeuroIS tools with accompanying acronyms is presented below (Figure 2). In this figure, the most commonly used NeuroIS tools are classified based on two dimensions: Ease of use (x axis) and Resource requirements (y axis). Ease of use is to be understood as the level of efforts required to use a NeuroIS tool: on the one hand, fMRI requires extensive efforts to set up and run, and considerable efforts to process the outputs of the device. On the other hand, a SCR requires significantly lower amount of efforts, since its use is much more natural to both experimenters and participants. The resource requirements scale should be perceived as the amount of resources (e.g. financial resources, infrastructure, manpower and time) required to successfully use a NeuroIS tools. For the purposes of illustration let us compare a PET and SCR on this scale: a PET requires a clinical level of infrastructure and comes with large upfront and running costs, which dwarfs the resource requirements for SCR. The listed NeuroIS tools in Figure 12 NeuroIS tools grouped together into clusters: Clinical clusters represent those devices which are mostly employed in a clinical settings; Lab clusters positioned between the Clinical and Office cluster since most of the devices that populate this cluster are commonly used in laboratory settings; Office cluster consists of those devices that can be easily used in regular office settings. Currently the illegal cluster is populated with invasive BCIs which are not approved for use by FDA at this moment (Engber 2016). Finally, the Plug & play area depicts all NeuroIS tools which require little to no special conditions and which are ready to use with little or no difficulties.

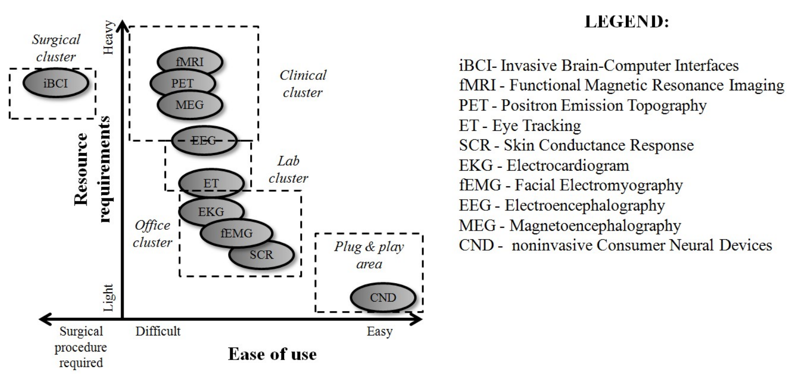


Figure 12: An overview of NeuroIS tools

Clinical, Lab and Office clusters have been used within the NeuroIS literature and the available body of knowledge that originates from those clusters is expanding. However, the Plug & play area represents uncharted waters for NeuroIS and for potential organizational and individual users of CNDs. Noninvasive CNDs are cheap and easy to use, but little is known about their research or usage potentials. Apart from few pioneering studies (e.g. (Kuan et al. 2014; Minas et al. 2014b)) NeuroIS did not employ consumer grade noninvasive CNDs extensively.

In order to further explore the Plug and play cluster, which is exclusively populated by noninvasive CND devices, this research provides a concise overview of different noninvasive consumer level CNDs. According to their respective manufacturers, those devices are potent to compliment NeuroIS research and organizational needs at relatively low resource demands, while being easy to use. One device from this cluster (Emotiv Epoc) was used in the previously mentioned study (Kuan et al. 2014).

All of the devices from Table 9 are extremely easy to operate when compared to the orthodox neural instrumentarium. After a simple driver and software installation, a CND is completely ready for use. Most of the devices from Table 9 support multiple operating systems (e.g. MS Windows, Apple OS, iOS, Android, Linux and/or Ubuntu) and provide either software or an API for collecting and storing raw neural data. In addition, those devices are extremely inexpensive compared to the commonly used NeuroIS tools. According to the manufacturers specifications and press releases, every single CND from Table 9 can be (or will be) available for purchase for well under a thousand US dollars.

Table 9: An Overview of CNDs

Name	Technology used				Manufacturer	Released
	EEG	EMG	ECG	EOG		
Open BCI Ganglion (R&D)	X	X	X		OpenBCI	Summer 2016
iFocusBand	X				iFocus	October 2014
Emotiv Epoc	X				EmotivSystems	December 2009
Emotiv Insight	X				EmotivSystems	August 2015
Muse	X				InteraXon	April 2014
Aurora Headband				X	Iwinks	July 2015
MindSet	X				NeuroSky	March 2007
MyndPlay	X				MyndPlay	December 2011
MelonHeadband	X				Melon	Nov 2014
XWave Sonic	X				PLX Devices	February 2013
MindWave	**X**				**NeuroSky**	**March 2011**
Mindflex	X				NeuroSky (Mattel)	December 2009
Neural Impulse Actuator		X			OCZ	April 2008

With that in mind and with an intention to test a CND, a pilot study with one of the devices from Table 9 was conducted. The selected device, Neurosky Mindwave headband (headband in the following text), was used to gather data from a group of 12 test subjects . Neuro Experimenter software v3.28 was used to access the API of the headband and to record EEG based CND data (Mellender 2016). All participating subjects of this pilot study were healthy PhD students at a medium-sized private university in the southern part of the United States. All subjects were right handed, and between ages of 27 and 35. Two participants were female. All recordings were gathered in a standard office environment, while subjects were working on light office tasks that required them to use a computer (e.g. checking email inbox, browsing the Internet and arranging files etc.). Participants were explicitly told to remove the headband as soon as they are done with their office tasks. According to the manufacturer's specification, Headband is able to detect Alpha 1, Alpha 2, Beta 1, Beta 2, Gamma 1, Gamma 2, Delta and Theta waves. According to manufacturer's specification, the headband used in this pilot study records brainwave readings every 500ms, via a "cluster sensor" positioned on the participant's forehead and targeted at the prefrontal cortex (PFC). PFC is known to be the executive center of the human brain (Dimoka 2012; Dimoka et al. 2011), where decision actions (e.g. calculations) are performed. Descriptive statistics of the gathered data are presented in Appendix E. In depth analysis of gathered data (e.g. outliers and ERPs) was omitted due to technical constraints of this venue of publication.

To sum, this pilot study demonstrated that a CND can be used to collect EEG signals. Naturally, spatial and temporal resolutions of the recordings are not identical to the standards that are generally employed in EEG studies (Müller-Putz et al. 2015a) –

instead of dozens of simple sensors, the headband used in this pilot study has only one "clustered sensor"; and instead of recommended 200ms temporal resolution this device is capable of recording only 500 ms intervals. However, according to criterions presented in Kübler et al. (2001), the headband used in this study fits all the requirements for a CND because it successfully detected the electrophysiological activity of the user's brain, recorded the signals at 97.62% accuracy (which is above proposed 70% threshold) and bypassed most of the stated limitations.

This pilot study paves the way for using CNDs to better understand and detects one of the growing technostress phenomena known as Information Overload (IO). IO can be defined from two perspectives. From the organizational perspective, IO occurs when the amount of input to a system exceeds its processing capacity (Speier et al. 1999) and thus causes negative or unwanted effects for the organization and its employees. For example, IO negatively influences social capital formation in organizations and causes "star employees" to fail to perform efficiently (Oldroyd and Morris 2012). To add to the problem, the amount of information processed by organizations grows exponentially - size of business related data today is 17 ZB (Oracle 2012), while the growth rate of corporately stored data grows by 40% each year (McKinsey 2011). Although organizations are reporting limited success in mitigating this problem by implementing alternatives for searching (Lau et al. 2001; Tams et al. 2014), visualizing (Turetken and Sharda 2001) or extracting content (Dale et al. 2005), individual IO problems are rarely addressed.

Regardless of not being well addressed, IO manifest on the individual perspective as well. Individuals experience IO as state in which vast amount of information is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation (Flew 2007; Graham 1999). In short, IO can be understood as a state in which there is just too much information to cope with (Sobotta 2016).

Thus it is not surprising that IO, propelled by a wide use of information technology and a growing digital immersion, is considered to be a rampant problem. Previous research seems to support a relationship between the proliferation of information technology and IO (Bawden 2001). Some technologies appear to be more potent than others when it comes to causing IO. Internet is commonly portrayed as the main cause of IO on both individual and organizational level, followed by classical telecommunication networks and intra-organizational information systems (Hu et al. 2009; Rutsky 1999).

The combination of these information technologies create tremendous Information Overload for average, digitally versed individuals – known as information age citizens. Specifically, an average information age citizen processes 122 emails per day (Radicati Group 2015), while actively using more than 5 accounts on more than 4 social networks. An information age citizen spends around 2 hours per day just to manage his/her social network presence (GWI 2015) and a contact network of around 350 members (Edison Research and Triton Digital 2015). In order to manage digital social networks, an information age citizen is recommended to post around 2 to 5 post per day - depending on the actual type of the used network (Pew Research Center 2014). Additionally, an average American processes around 40 SMS messages and 12 voice calls per day. Those numbers are significantly greater when it comes to younger population – who process around 170 SMS messages per day (Pew Research Center 2014).

With all that in mind it follows that IO puts a tremendous strain on individuals and on individual cognitive performances – especially on the short term memory function of the human brain and on the executive center of the brain located in the pre frontal lobe (Dimoka 2012; Fuster et al. 2000; Goldman-Rakic et al. 1996; Riedl, R. Banker, et al. 2010). In previous research, a set of clinical grade instruments, like a FMR scan or EEG were used to further the understanding of the human brain (Dimoka, Banker, et al. 2010). However, IO would be rather difficult to induce in the clinical/lab environment and potential results might be unusable for practitioners. Therefore, if we are to detect and treat IO in real-life scenarios a more mobile and wearable technology is needed. CND seems to fit into that description perfectly. With that in mind, a study with two different consumer level neural interfaces (Epoc Emotiv and Neurosky Mindwave) is proposed. Ideally, author hopes that the mentioned study will provide additional insights about detection and prevention of IO overload through the use of CNDs.

This research brings multiple contributions. Firstly, it provided a concise insight into the current state of NeuroIS field. Secondly, a classification of commonly used neural tools is proposed (Figure 2). In it, different neural tools are grouped on the basis of resource intensity and ease of use, which lead to creation of five distinct clusters. Thirdly, special attention has been given to one cluster which was not used as widely as the other clusters and an overview of different noninvasive consumer grade CNDs has been provided (Table 7). Fourthly, this research conducted a preliminary study in which a CND is used to collect and process brainwave readings. And finally, this research proposed a potential study in which CNDs can be used to detect, prevent and better understand a rampant information age problem of information overload.

In conclusion, this research might on the one hand encourage the novice and prospective IS researchers to consider joining the growing NeuroIS community by adding neural tools from the resource light and easy to use Plug & play cluster into their research. That should, ideally, allow novice research to circumvent seemingly overwhelming demands imposed by the sheer complexity of neuroscience. On the other hand, I hope that this research might point the attention of NeuroIS veterans and practitioners to a research worthy and partially neglected phenomena of noninvasive consumer level CNDs.

As Milic (2017) posits, clinical environment are limiting the potential to research real world phenomena not only by daunting financial requirements and required technological expertise but also by the need of clinical environment. However, the mono polar CND used in the aforementioned study is capable of detecting EEG signals in a way which is methodologically comparable to some seminal EEG studies (e.g. Berka et al. 2007b; Gevins and Smith 2006; Holm et al. 2009; Kramer 1990; Pope et al. 1995). Thus, Hypothesis 3 presents the following:

> *H3: Consumer Neural Devices are capable of detecting specific IO related brain states using the constructs tested on clinical neural devices.*

CHAPTER THREE

Methodology

This dissertation employs a within group experimental design on 61 participants to answer the research questions stated in the introduction and test the hypotheses provided in the previous chapter. This experiment uses data supplied from a Consumer Neural Device (CND) and oximeter, system data and data from the paper sheets given to the participants. The basis of this experimental design is manifold. To begin with, this experiment builds on the observations made in the introductory chapter of this dissertation, which are further enhanced by my own stance on practitioners' positions. This experiment also builds on Chapter Two of this dissertation by providing more information on how the questions of interests, theoretical mechanism and hypotheses for this experiment were developed and grounded in the literature. In this chapter, I discuss the rationale of using CNDs, experimental design and technical details behind data collection.

The experiment used in this dissertation consists of multiple data sources and multiple types of stimuli. I have collected sensory data supplied from the CND and oximeter, system data (i.e. system time) from the computers used to run the experiment and, where available, textual data from the paper sheets that were given to the participants. To the best of my knowledge, a pre-set methodology that can fully encompass and create a mechanism for Information Overload experimentation using CNDs does not exist. This situation is further complicated by the need to include different forms of data, specifically CND readings, oximeter supplied information and textual data coming from the paper notes.

The scientific method I use consists of techniques for investigating phenomena, creating new knowledge, augmenting or correcting existing knowledge and integrating new findings with the existing ones. The goal for this dissertation is to create new knowledge and to integrate new findings into the ongoing scientific discussion in the Information Systems field. In order for it to be classified as scientific and thus positivistic, this method of inquiry has to be based on empirically measurable evidence and subject to specific principles of reasoning. The scientific method is an ongoing and iterative process. It starts from making observations (which are explained in Chapter One), through selecting areas of interest, formulating theoretical mechanism, developing testable predictions in form of hypotheses (Chapter Two), gathering data to test those predictions (Chapter Three) and either organizing the findings to produce new knowledge (Chapters Four and Five) or redesigning the study. I now proceed with proposing a standard for CND experimental procedures, discussing the rationales behind using CNDs and continue by arguing for the manner in which a CND is used in this dissertation under the paradigm of the methodology I have summarized in this sub-chapter.

Experimental Procedures

This study pioneers the use of neural constructs and correlates from cognitive neuroscience through the means of CNDs with intent to further the IS knowledge, settle the open debates and fill the gaps in IS literature. As a result of the novelty of this venue of exploration, established instrumental procedures are not in existence. Thus, to build a comprehensive set of instrumental procedures for this research, I incorporate the procedures developed for clinical EEG devices. Specifically, I rely on two seminal works: one written specifically for an IS audience (Muller-Putz et al. 2015) and the other used for medical researchers (Keil et al. 2014). Muller-Putz et al. (2015) explain the fundamentals of using EEG based constructs in IS discipline. They also state that a clear set of comprehensive EEG procedures does not exist. In the same work, Muller et al. (2015) highlight the fact that different fields like psychophysiology, clinical neurophysiology and cognitive neurosciences have "enormous thematic depth" (p. 928) and vast amount of diverging procedures. They also summarize the principles behind reporting EEG studies in NeuroIS research (p. 929). I use their work to ground my instrumental CND procedure. I also consult Keil et al. (2014) to expand the understanding of the procedures and to fine-tune it for CND usage.

Both sources argue for clearly stating hypotheses and theoretical background before putting the experiment in motion. The same sources also highlight the need for obtaining informed consent, providing information about sensor types and locations. And these two sources agree about reporting participants' major characteristics, experimental instructions, equipment, protocols and stimuli. Both sources also agree on the need for reporting data preprocessing and segmentation details. Moreover, Keil et al. (2014) focuses deeply on the technical details of the equipment by advocating for explanations of spatial sampling, measuring sensor locations, reporting amplifier type, impedance levels and recording settings.

Most of their recommendations are completely applicable for CNDs, with some exceptions. For instance, since the actual configuration of a CND is not modular, unlike the configuration of a clinical EEG device, I posit that a detailed description of the equipment should be procedurally addressed by describing the hardware behind the used CND. Furthermore, in most cases the experimenter is not able to access the data from the CND on the same levels on which the data can be accessed from the clinical devices. Similarly, to fulfill their function as consumer devices, all CNDs are equipped with some data preprocessing mechanism. In other word, the data supplied from a CND is not as "raw" as the data supplied from a clinical device. With that in mind, I propose a preliminary set of instrumental procedures for using CNDs in NeuroIS research. These procedures are presented in Table 10.

Each procedure was addressed in detail for this study. The theoretical grounds were established in Chapter Two. CND and the corresponding software are presented in Appendices A and B respectively. This chapter provides detailed information on experimental protocol, experimental stimuli, and data collection, as well as construct and participant specification. Highly detailed explanations of experimental protocol are further discussed in appendices C and D. And data analysis is discussed in the next chapter of this dissertation.

The Rationale of Using Consumer Neural Devices

This dissertation uses CNDs for multiple reasons. Most importantly, using CND comes with the loosen use requirements, which allow researchers to approach the topics that cannot be truthfully or meaningfully simulated in clinical environments. These loose requirements further empower researchers to use the experimental settings which either completely or to a significant degree match the settings in which the phenomenon occurs.

Table 10: CND Instrumental procedures

Procedure	Description
Theoretical grounds	A precise and comprehensive explanation of a congruent theoretical model or mechanism is necessary for every CND study. CND's can be used for explorative purposes, but not for exploring new neural correlates since the technical characteristics of modern CND's can produce usable data for existing constructs (Straub et al. 2004) but not the data with enough internal consistency needed to build new constructs (Cook and Campbell 1979).
CND specification	Technical details of CND and corresponding software which is used in the study should be presented with the study, or referenced directly from the manufacturer's manual. Bases on which the connection between the capabilities of a CND and the capabilities of a comparable clinical tool are argued should be explicated and mapped to the terminology used for clinical devices (i.e. 10-20 EEG system).
Construct specification	Each construct which can be measured through the means of a CND should be specified in full and mapped to current standards applicable to comparable clinical equipment.
Participant specification	CND studies should describe participant's general characteristics as well as the characteristics which are specific for the specific study.
Experimental protocol	Comprehensive description of experimental protocols should be reported. This report should include instructions and an overview for the CND experiment used in the study.
Experimental stimuli	All experimental stimuli should be made explicit and presented in sufficient detail.
Data collection	CND studies should report what construct was measured and in which manner.
Data analysis	Before a statistical instrument suited for the study is employed a descriptive statistics for the collected data should be provided.

These loose requirements further empower researchers to use the experimental settings which either completely or to a significant degree match the settings in which the phenomenon occurs. To deepen the problem, the design of clinical devices causes Hawthorne effects more frequently than the design used in CNDs. In other words, it can be expected that the alteration of behavior by the subjects of a study due to their awareness of being observed will be pronounced more in clinical than in regular office settings used for CNDs. I posit that a clinical environment would not only limit the naturalness of the environment but could also create severe data noise as a result from environment-induced stressors. For example, multiple studies have shown that introducing the participants into a clinical settings can increase stress levels as measured by the cortisol levels in participants' saliva (e.g. Kirschbaum et al. 1996; Riedl 2012; Tams et al. 2014) beyond the levels where data normalization and filtration is possible.

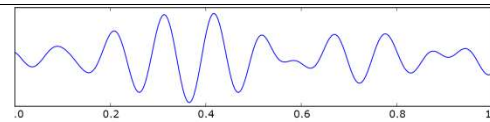
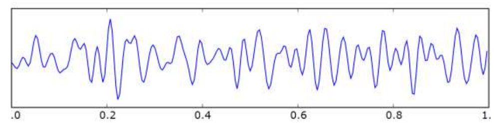
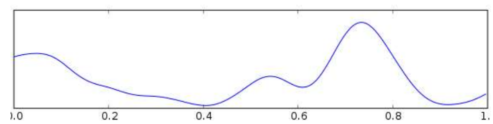
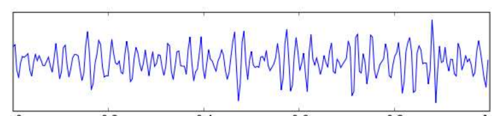
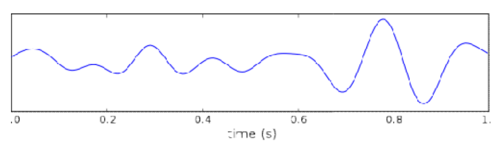
Moreover, clinical instruments come with high research costs and steep learning curves (Milic 2017). If the standardized clinical equipment was used in this dissertation, it would be harder to make this experiment readily scalable for potential future re-runs and modifications. This restricts IS researchers at smaller institutions or developing countries from the academic debate and thus greatly limits the audience for NeuroIS. Another reason that motivates the use of CNDs stems from the noticeable discomfort which comes from the lack of ergonomics generally accompanying clinical devices. For example, even a modest 10-20 EEG equipment would require participants to have multiple gel covered electrodes on their heads. Ergonomics aside, the danger of stressors contaminating data remains present. Furthermore, even if all the stated reasons are deemed as irrelevant, there is simply no need to use the clinical devices as most of the collected data would end up being unused since the neural correlates that are used to detect and define IO, namely cognitive workload and task difficulty, are generally measured by the use of mono-polar EEG setting consisting of one grounding and one sensory electrode (Kramer 1990). The CND used in this dissertation is designed to fulfill these requirements for mono-polar setting, as explained in Appendix A.

The Implementation of Consumer Neural Devices

The implementation of CNDs in this study follows recommendations provided by Mellender (2016) and protocol design proposed by Muller-Putz et al. (2016). Instead of a Thinkgear connector, which is provided by the device manufacturer, I use a third party open-source solution named NeuroExperimenter (NEx). Unlike the official software, NEx accesses the CNDs application port interface (API) to collect the data in the raw form. This allows researchers to export the data from the CND API and perform a range of statistical analysis. The original software does not support nor allow any form of data extraction, as of April 2016. NEx also enables exporting of the full data gathered from the CND amplifier. For detailed technical information about this software, please consult Appendix B.

CND used in this dissertation provides raw data at the frequency of 512 times per second. Therefore, the CND's temporal resolution provides a good ground to detect neural phenomena and to compare it with the clinically recorded elements. This raw data consists of the following categories: Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, Gamma1, Gamma2, Blink and Power. The first eight categories are marked by Greek letters and represent the corresponding EEG waves. These categories are standard throughout EEG literature, although some authors argue for a slightly different frequency bands (Pizzagalli 2007). The table below provides more information about the recorded EEG frequencies as classified by the CND's manufacturer.

Table 11: EEG frequency bands

Frequency band	Bandwidth (Hz)	Associated mental states	Illustrations (wiki-commons)
Alpha 1	8-9	Mental coordination, calmness, readiness,	
Alpha 2	10-12		
Beta 1	13-17	Fast idle, or musing	
Beta 2	18-30	High engagement, focused attention, complex thoughts	
Delta	1-3	Deep sleep, coma, empathy	
Gamma 1	31-40	Arousal, performance zenith	
Gamma 2	41-50		
Theta	4-7	Vivid dreams, meditation, drowsiness	

Blink data points measure the strength of the electronic impulses generated by the contraction of ocular muscles during the action of blinking, while the Power data points record the sum of all electrical changes. The Power category is crucial for normalizing the data and for making it mutually comparable for different individuals. According to the manufacturer's manuals, the power values are not represented in SI units, but in relational terms. As such, these readings are only useful when compared to each other for the purposes of analyzing temporal aspects and relative quantity of power oscillations.

This device also records “eSense” data in the form of Attention and Mediation variables once per second. However, the “eSense” data points are not real raw data even though they are reported by the device with the rest of the real data. The manufacturer claims that “eSense” values are calculated on scientific basis, but the actual formula behind that calculation has not been made available to the public, as of November 2015. As it is not possible to ascertain if “eSense” data points are produced in a rigorous and scientifically grounded way, this dissertation refrains from using any of the “eSense” data in any manner. Furthermore, NEx has proven to be more efficient than the standardized EEG signal processing tools since it does not report the data in the initial form, but only after the Fourier transformation is used and only after the signals are amplified. I believe this is particularly convenient for IS studies, since neuroscience as a discipline still have not reached an agreement on how to clean and normalize the initial form of EEG signals (for ongoing discussion on this topic please consult Babiloni et al. 2011; Bazanova 2012; Clapp et al. 2012; Freyer et al. 2012; Hung et al. 2013; Landsness et al. 2011) and since IS researchers simply do not have the expertise to join or resolve neuroscience debates.

All NEx provided data is recorded as it is received. After data points are received, the processed data used in the report log is buffered and accumulated. When data is supplied to NEx, the data points corresponding with the actual neural event are placed in the buffer. To avoid overwriting the buffered data, new data is not written in the output file until new data points are supplied by the device. Timestamps of each data point are based on the system time at the moment of receiving the specific data point. Timestamps for the log data are further normalized to one second epochs to allow full comparison of CND supplied data points with the data points supplied from the oximeter. In situations where participant does not blink, the Blink data point will remain unreported. The same result occurs when CND does not supply any other data point. This pattern of reporting does not handicap the implementation of CNDs in the experimental settings as long as data is screened and cleaned out of these anomalies.

However, the manner in which CNDs are implemented to collect data in this experiment has its limitation. To begin with, it is impossible to record multiple blinks if these blinks occur in epochs which are shorter than one second. This pattern of reporting limits the usability of CNDs in studies where multiple blinks per second are to be reported. Since theoretical constructs and the corresponding neural correlates for Information Overload (IO) do not require absolute precision in recording eye blinks, this does not restrict the usage of the CND in this context. Next, the meanings of specific brain waves are related to the spatial coordinates of their occurrence. Since CNDs have significantly smaller spatial resolution compared to the medical grade EEG tools, this limits their ability to measure constructs which require multiple sensory locations. However, this dissertation uses constructs of cognitive workload and task difficulty which are also established in the mono-polar EEG settings with low spatial resolutions and within the spatial coordinates used by the CND (Holm et al. 2009; Kramer 1990).

Experimental Design

Experimental design is crucial for this dissertation for three reasons. In classical experimental settings, without a precise control of all external and internal factors influencing the experimental outcomes it would be impossible to link the neural measures with the stimuli that are provided by the experimenter. However, I posit that controlling for all known and unknown factors which can influence Information Overload is unrealistic. That is why I use a randomized experimental design (Brown and Melamed 1990) and assume that extraneous sources beyond my control (i.e. participant's anatomic and genetic factors, weather, health condition, sleep deprivation etc.) are randomly distributed throughout the population. Next, to assure that experimental results are not caused by unwanted order effects (i.e. Galesic et al. 2008; Hogarth and Einhorn 1992; Schwarz et al. 1992), all but one experimental stimuli are presented to the participants in a random fashion. Experimental design is also important for reasons of replicability. Precisely defined and thoroughly detailed design allows future studies to replicate this experiment as thoroughly and as fully as possible and to easily compare the future findings with the results of this dissertation. This design characteristic can be used to compare the results coming from the CND used in this study with other CND's or, optionally, with other clinical instruments which are not obtrusive to the experimental tasks.

The experiment used in this dissertation builds from 2 x 2 experimental framework presented below (Figure 13). This framework compares two groups of participants, namely Digital Migrants and Digital Natives, in two elicited experimental states: one where information influx is low and the other where IO is induced. The four quadrants of this experimental framework thus represent four different scenarios based on two groups of participants and on two groups of information influx. The upper left quadrant represents a set of events in which Elementary Cognitive Performances (ECT) of Digital Migrants are being measured by CND while IO is induced. Similarly, ECTs of

Digital Natives under IO are positioned in the upper right quadrant. The bottom right and left quadrants stand for the portion of the experiment which tests ECTs of Digital Natives and Migrants respectively under the situations in which the information influx is low. Testing Hypothesis 1a is conducted by analyzing the variance of experimental results (i.e. neural readings and textual data from paper notes) between top and bottom row of this framework, while the Hypothesis 1d is tested by analyzing the variance between the results of left and right columns of this framework.

	Digital Migrants	**Digital Natives**
Information Overload	Elementary Cognitive Performances of Digital Migrants under Information Overload.	Elementary Cognitive Performances of Digital Natives under Information Overload
Normal Inf. Influx	Elementary Cognitive Performances of Digital Migrants under normal Information Influx.	Elementary Cognitive Performances of Digital Natives under normal Information Influx.

Figure 13: Experimental Framework

The experimental framework provides a high level tool for understanding the general elements of the experimental design and for testing two hypotheses. Other hypotheses are tested by analyzing the variance which occurs between different experimental stimuli. Figure 14 illustrates four different experimental stimuli.

All stimuli are transcribed in full in Appendix D. All graphical interfaces leading to stimuli are presented in full in Appendix C.

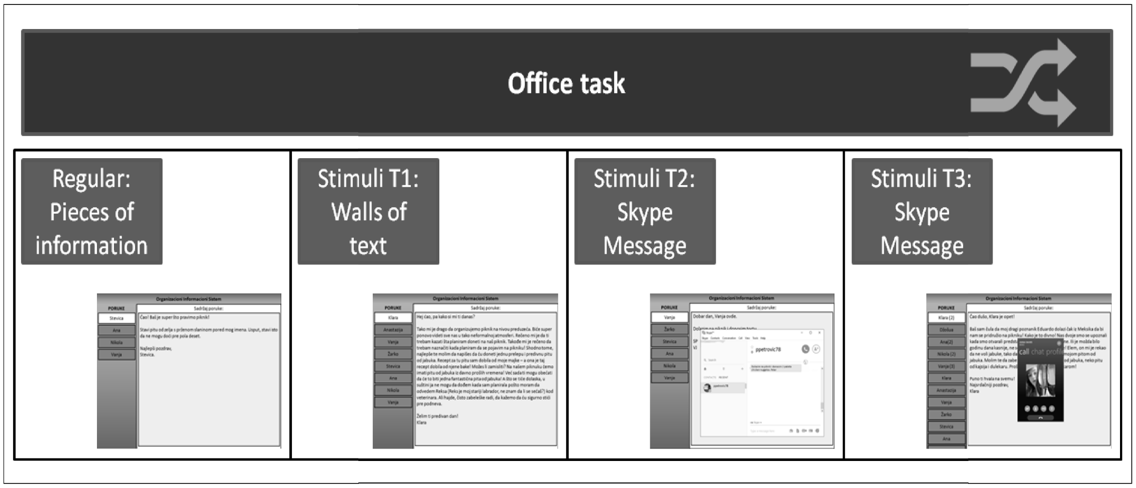


Figure 14: Experimental Stimuli

Small pieces of information (i.e. short messages) are used to provide base data for comparing the low information influx states with states where IO is induced. Other stimuli are used to induce IO in participating individuals. Hypotheses 1b and 1c are tested by analyzing the variance between the experimental results between these two states. Hypotheses 2a and 2b are tested by analyzing the variance between different IO stimuli. On the one hand, when it comes to Hypothesis 2a, assuming task fitness, the richer the information is the smaller the effects of IO on ECTs are expected. Therefore, a richer information medium like a voice message should cause smaller effects on ECTs compared to a leaner information medium like a brief textual message. On the other hand, the more natural the information category is, the smaller the effects of IO on ECT should be. Thus, information presented in a natural way (i.e. voice) should produce smaller effects compared to a less natural presentation like email. Hypothesis 3 is tested by comparing the data patterns collected with the CND to the publicly available EEG patterns provided by clinical equipment.

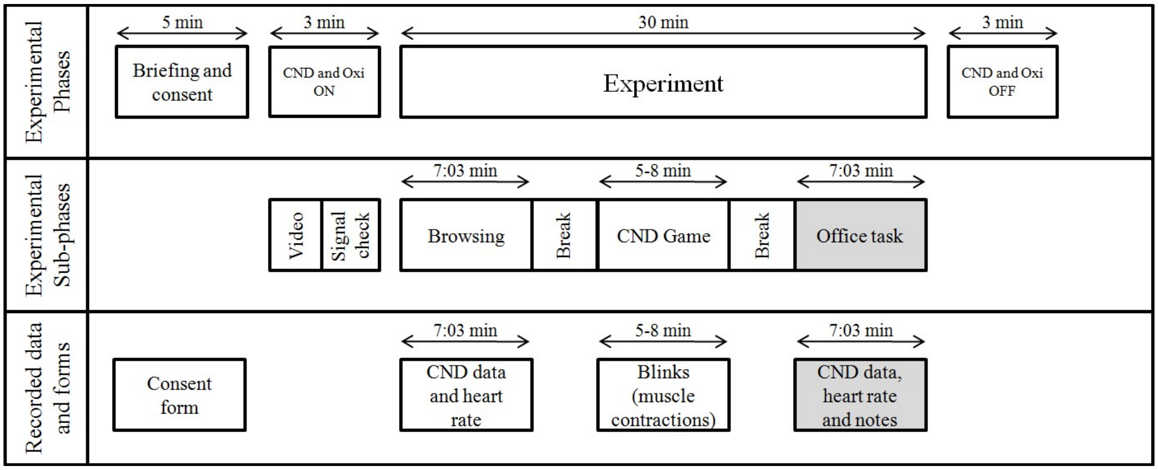


Figure 15: Experiment Overview

Figure 15 shows different experimental phases, sub-phases, and recorded forms of data. The experiment starts with briefing the participants about the purpose and main goals of this dissertation. After the participants are informed about the study and the experimental procedures it entails, a consent form is provided. Special care was taken to ensure that individuals understood that they were free to decline to participate in this experiment. Similarly, I also made it explicit that the participating individual could stop the experiment whenever he or she desired. After signing the printed consent form, the participant was asked to watch a specific video clip. This video informed the participants how to mount the CND on his or her head. Upon successful mounting of the CND, the experimenter mounted an oximeter on the participant's non-writing hand index finger. Mounting an oximeter to the participant's writing hand could distort the oximeter data, which is used to control for potential stressors, and limit the participant's ability to take notes coming from the simulated system.

Before running the experiment phase, the experimenter performed the signal checks. When CND or oximeter signals are missing, the participant was instructed to mount the experimental equipment again. If signals were missing after three attempts, the participant was dismissed. In this dissertation, I refrain from discussing why the signals could be missing. Potentially, participants could have also been dismissed by failing to follow the participating procedures, as detailed in the Selection of Participants section of this chapter, and by having abnormal pulse readings (i.e. if having a heart condition or experiencing high levels of stress). However, participants were not dismissed if they did not fill the provided sheets. The reasons for this are explained in detail in Chapter Four.

Once the experimental equipment was mounted and signals verified, the experimental phase began. This phase consisted of the following sub-phases: Internet browsing, CND game, Office task and breaks. In Internet browsing sub-phase, participants were required to browse the internet while having their signals recorded. These recording were used to further test if the equipment is properly mounted and to create base readings needed for processing CND data. This sub-phase lasted as much as the central sub-phase (shaded). After a short break, the participant was introduced to CND based games. These games use the participant's brain waves and blinks to control the on-screen character or event. The games were used for the following reasons. To begin with, the games were used to make the participant more relaxed. This further prevents potential remaining stressors to influence the readings in the next sub-phase. Next, games allow the participant to get a "sense" of how the CND actually works. And most importantly, these games enable the researchers to measure the strength of the blinking signals. This is particularly important since blinking signals, if not treated properly, can pollute the data reported by the CND. After this phase was completed, participants were again instructed to rest for few minutes.

The most important sub-phase of this experiment was the Office task. This sub-phase required participants to organize a company-wide picnic list by writing down names of the participants, times of arrival and the food items which picnic attendees will bring. The participants also had a special rubric named “notes”, in case they wanted to write additional content down. In this sub-phase, participants were introduced to the simulation of an organizational information system. This system simulated a digital environment in which employees could exchange information inside an organization. To ensure participants understood how to use this system, a short tutorial explaining the use of the system was presented. The graphical user interface of the simulation is presented in Appendix C. The contents of the tutorial and the messages displayed through this system are presented in Appendix D. Since the functionalities and logic of this system are very common and basic, comparable to using an email client or Facebook, participants were not required to complete any tests to prove their understanding of the functioning of the system. After 60 seconds, the tutorial ended and participants were informed that the system simulation is about to begin. Ten seconds later the first simulation screen was displayed to the participants.

Every participant was introduced with an identical first message. After this initial message, a series of stimuli were presented to the participant. The main experimental stimuli used in this experiment are low information influx messages and messages designed to induce IO. The later messages fall into three categories: messages with a large amount of text (“Wall of text”), voice messages (“Skype voice”) and chat messages (“Skype chat”). To eliminate the potential order effects, these messages were presented randomly, with “Wall of text” messages being the sole exception. Since all three “Wall of text" messages are connected to each other by a storyline, it would be meaningless to present them in a random order. When this sub-phase of the experimental phase was completed, the participants were instructed to remove the experimental equipment from their heads and fingers. The initial design of this experiment included a set of qualitative interviews after the experimental phase. Unfortunately, most of the participants were too tired to provide usable qualitative data at that point. For these reasons, I decided to remove that part of the data collection altogether.

During each experimental phase specific types of data, like heart rate, blink impulses and EEG recordings, were collected. To begin with, in the briefing and consent phase I collected written consent forms (Appendix G). During the experiment phase, the following data was collected and/or processed: heart rate, blink impulses and full CND data. The blink data collected in the CND game sub-phase was used to fine tune the instrument so that the electric potentials coming from blinking would not pollute the data for office task sub-phase. During the office task sub-phase I collected CND data, heart rates and participant's notes. For additional information about oximeter and textual data, please consult Appendix E.

Level of Analysis

The research mechanism used for this dissertation is based on the Theoretical Mechanism of Information Overload I presented earlier. As discussed earlier, this mechanism is build on the base of IRT and INT. Information Richness theory has been used at both organizational and individual levels, while the Information Naturalness theory has been almost exclusively used at the individual level of analysis. With that in mind, this dissertation employs an individual level of analysis. More specifically, all participating individuals in this experiment are understood as separate single entities for the purposes of statistical processing and analysis.

Selection of Participants

I personally recruited all the participants in this study. One local business and non-government organization graciously helped me in my recruiting efforts and in providing direct incentives for recruiting the participants. Baylor Information Systems department also provided some volunteers for this experiment. All non-faculty participants who successfully completed this experiment were given equal chances to win material incentives of approximately 500 USD in total after the completion of the study. The following criteria were used in selecting the participants: age, basic computer literacy and health condition.

All participants in this study are 18 years old or older. Although individuals younger than 18 years could have easily completed the required tasks, I did not use them for this study because of ethical, procedural and attention span reasons. Furthermore, since one of the basic concepts tested by this study relies heavily on age, recruiting activities were orchestrated to attract roughly equal numbers of Digital Natives and Digital Migrants. As it is stated in Chapter One, this dissertation understands all individuals born after 1980's and exposed to information technology since early age to be Digital Natives. Similarly, the population which was born before 1980's is understood as part of Digital Migrants.

Basic computer literacy is crucial for conducting the experiment phase of this study. That is why all participants have been screened for basic computer literacy skills. In particular, all participants were asked if they have used a digital device before (i.e. a desktop, laptop, mobile phone or tablet) and if they feel like being at least basically proficient in using software with graphical user interfaces. Only one participant was dismissed as a result of potentially inadequate computer literacy.

Finally, all participants were asked if they know any personal medical conditions that might prohibit them to participate in this study. Although there are no grounds to believe that participating in this study could harm anyone, potential severe health conditions (e.g. schizophrenia, as described in Light et al. 2015; Rissling et al. 2014) could pollute the data. Not a single participant has reported that he or she feels incapable to participate in this study. In addition to the general health related questions, participants were also told not to consume any psychoactive substances or high doses of caffeine or sugar at least 24 hours prior to the start of the experiment. Participants were also informed that they should get plenty of sleep the day before the experiment, given that the lack of sleep is known to significantly alter the EEG readings in clinical devices (i.e. Felten et al. 2015; Hung et al. 2013; Landsness et al. 2011; Lopes da Silva 2004). All participants verbally confirmed that they have followed these suggestions in full. I did not test the participants to control for these factors, since the control would have to include blood sampling which is neither a comfortable nor non-invasive procedure and, as such, would be in violation of the basic premises of this dissertation.

Participants' Demographics

For the purposes of the experiment, I recruited 98 participants ages 19 to 81. Due to the reasons explained in the previous parts of this chapter, only 61 participants were used to record neural data. The participants' pool is heavily skewed towards Digital

Natives, since only 12 Digital Migrants reported for participation. Demographic details of for the participants are provided in the table below.

Table 12: Participants' Demographics

Characteristic	Number	Percent
Total participants	61	100%
Digital Migrants	12	19.67%
Digital Natives	49	80.33%
Average age	25.66	-
Gender	37 female/24 male	60.66% female/39.34% male
Left handed	7	11.48%
Right handed	54	88.52%
Education		
High school diploma	41	67.21%
College diploma	3	4.92%
Graduate diploma	13	21.31%
Other	4	6.56%

Data Collection

Experimental procedures set forth in the earlier parts of this chapter demand for a clear and thorough description of data collection details. This sub-chapter follows suit. The procedural specifics for data collection are presented bellow.

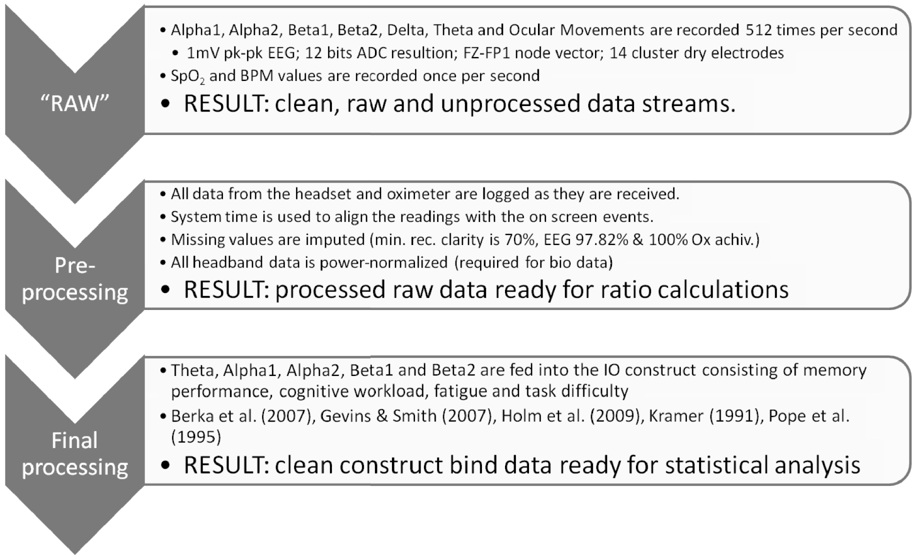


Figure 16: Data Collection Overview

Data collection process starts with the CND collecting the "raw" data from the electrical activity at FP1 sensor coordinate and A1 grounding electrode coordinate (picture below, shaded). The results of this phase of data collection are clean, "raw" and unprocessed data streams. The second phase of data collection is pre-processing the data which was collected from the used equipment. There are two crucial steps in this phase: aligning the data stream with system time so that the experimental stimuli can be linked with the neural measurements and imputing the data where values are missing or distorted. Interestingly, the CND used in this dissertation was capable of providing the signal clarity of 97.82% which is well above the clinical standards of 70%. The results of this phase are processed data streams which can be plugged directly into the established neural correlates. Final processing segment of data collection consists of plugging the neural readings into the existing neural correlates. Data which is collected and processed in this way provides a starting ground for data normalization, explanation of the collected measurements and application of neural correlates.

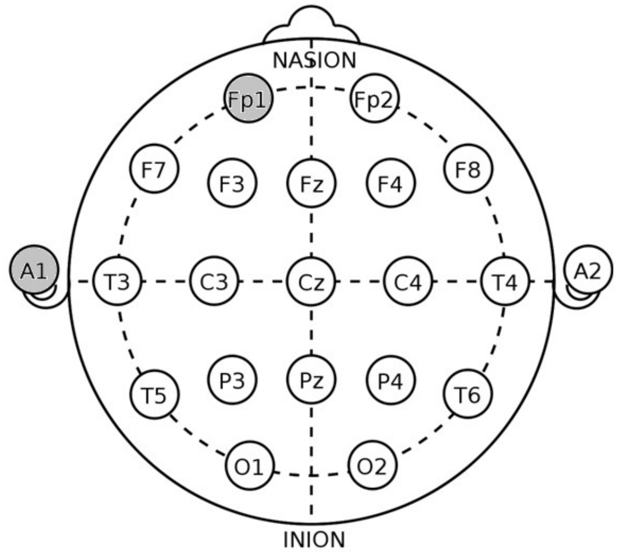


Figure 17: EEG sensor locations

Data Normalization

As a result of different conditions during which CND's sensor rests on the skin of the participants, it is possible that data points between multiple participants or sessions are not directly comparable. Mellenger (2016) confirms this variability. There are two ways in which this problem can be mitigated. The first is to assure that all experimental procedures are strictly followed for each participating individual. This minimizes the potential data disturbances coming from factors which are in experimenter's direct control. The second is to normalize data points before applying statistical tools for analyzing the data. The NEx is designed to normalize the power data by summing all the power data points first and by add dividing each power datum in the selected sample by total power supplied from CND's API. NEx latter applies the logarithmic normalization for all data points to ensure that the data logs are normalized. The figure below shows the results of data normalization procedures between non-normalized and normalized data collected for the purposes of this dissertation. Non normalized data on the left is characteristic for bio data, while the normalized data on the left is suitable for statistical analysis of variance needed for testing the hypotheses. Identical normalization process is used for all other EEG frequencies.

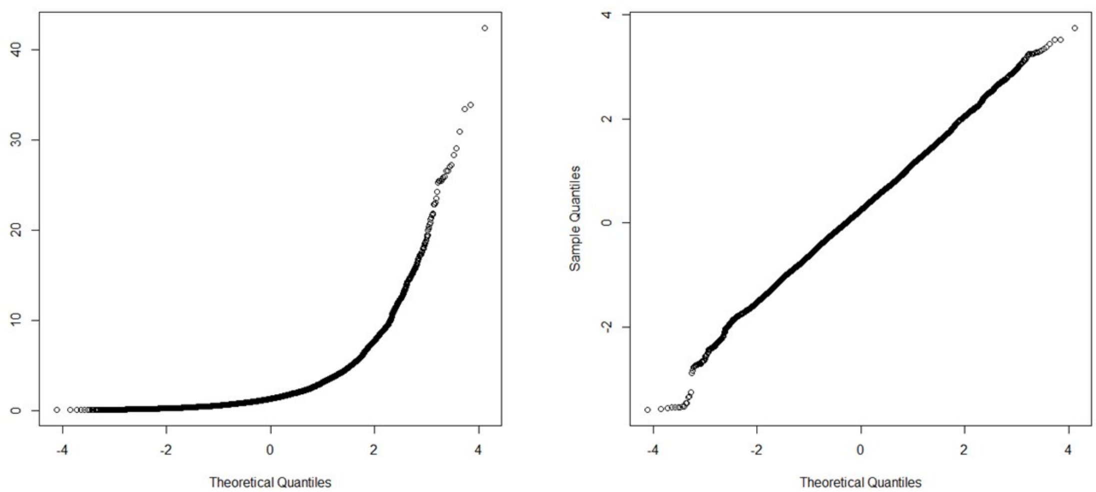


Figure 18: Non-normalized and normalized data

Measurements

For the purposes of this dissertation, I have recorded the following measurement from the CND's API: Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, Gamma1, Gamma2, Blink and Power. I have also collected heart rate and SpO2 measurements from the oximeter in parallel, as well as written notes from the participants. To ensure that these measurements can be tied to specific stimuli, each measurement was collected using the same system time. In terms of the neural data which is collected for the IO experimental sub-phase, this means that 5076 aggregated (post-processed) data points are collected per each participant. The descriptive statistics for these measures are provided below.

Table 13: Descriptive Statistics EEG

EEG Band /Variable*	Min	1st Qu.	Median	Mean	3rd Qu.	Max
Alpha1	94	3950	8230	13362	16401	52899
Alpha2	262	3947	7606	11829	14624	191770
Beta1	172	3841	7398	11490	13178	615322
Beta2	366	3950	7116	9532	11459	299266
Gama1	129	1923	3428	4633	5742	134983
Gama2	83	1218	2256	3072	3963	67819
Delta	377	12951	34210	143470	107580	3171503
Theta	772	13636	25805	44735	51700	953866
Power*	7102	67332	112444	242121	229151	4257343
Blink*	0	0	0	4.537	0	255

Neural Correlates

The neural correlates link the data streams from the experimental equipment with the established constructs from the cognitive neuroscience literature. To make these links possible, a key concept from the theoretical mechanism that corresponds to the neural correlates must be presented. For this dissertation, that key concept is elementary cognitive performance (ECT) through which the level of IO is measured. More specifically, I define my individual variable of ECT as basic tasks which demand only a small set of mental processes and which have easily specified correct outcomes. Similarly, I understand IO as a state in which individuals experience information influx and have a vast amount of information that is readily available, almost instantaneously, without mechanisms to check the validity of the content and the potential risk of misinformation. Both of these key concepts are presented in detail in Chapter Two.

To build the link between ECTs and IO, I employ two established constructs from cognitive neuroscience: cognitive workload and task difficulty as defined by Kramer (1991) and Pope et al. (1995). These two neural correlates stem from the environments which are similar to the experimental environment used for this dissertation. Furthermore, these two neural correlates have been tested with mono-polar EEG systems which use FP1 and A1 EEG coordinates on 10-20 EEG system map. This setting renders these constructs suitable for the CND device I use in this dissertation.

In order to use the correlates of cognitive workload and task difficulty a specific ratio has to be calculated. This ratio is defined by the formula presented below:

Equation 1: Information Overload Ratio

$$R_{io} = \frac{\theta}{\alpha h + \alpha l + \beta h + \beta l}$$

Therefore, to calculate the extent to which IO influences ECTs the data stream coming from the Theta EEG frequency band has to be divided by a sum of high and low Alpha and Beta EEG frequency bands, known as Alpha 1, Alpha 2, Beta 1 and Beta 2 respectively. The higher the value of this neural correlate, the greater the ECT effects coming from the IO are. Vice versa, the lower the value of the ratio, the lower are the effects of IO on ECTs.

CHAPTER FOUR

Results

This chapter uses one way analysis of variance (ANOVA) to test the hypotheses formalized in Chapter Two. Before the ANOVA results are presented, I discuss data screening procedures, correlate summary, correlate validity and testing for potential stressors. This chapter concludes with the formal results of hypotheses testing and discussion of these results.

Data Screening

As I explain in Chapter Three, I screened the data I have collected from three sources: CND, oximeter and paper notes. To assure each data source is accurately coded and represented, I have performed data cleansing on the digital portion of data. Specifically, I imputed average values for all missing CND readings. As reported in the previous chapter, CND failed to record the full EEG band in only 2.18% cases. Imputing values on such a small subset of the total data set is known not to cause any problems with statistical analysis (Hair et al. 2010). The oximeter I used did not fail to record any values at any point in time. Furthermore, it is known that ocular movements can distort the CND readings. That is why I have removed all data instances in which the spikes in neural correlate were caused by excessive blinking and inserted average values in missing places.

Correlate Summary

Regardless of the chosen technique, presenting neural data is a challenging task. To begin with, a complete and concise tabular representation is impossible, especially because of the volume of the collected data. Descriptive statistics presented in the previous chapter can provide a rough understanding of the collected data but the sheer richness, trends and many other properties of the dataset are left buried in the data. Additionally, the amount of the raw data is so great that its actual visual representation is technically impractical. For example, as a result of 512 Hz frequency, the rawest data for the Office-task experimental sub-phase coming just from the CND used for this dissertation contains the population of 110,886,912 observations, while the total data set for the entire experiment contains well over 350 million observations[1]. It goes without saying that a complete visual representation of the data pool of that magnitude is impractical for digital formats and impossible to implement for the printed formats. Furthermore, even if it would be possible to report that vast amount of data in verbatim, it would be very hard for the reader to comprehend the meaning behind that dataset. Similarly, well know statistical instruments start to fail when faced with datasets of similar sizes (i.e. according to Rahmand and Govindarajulu (1997) a standard normalization test, known as Shapiro Wilk, cannot process datasets which contain more than 5000 observations). That is why I do not perform the analysis of data in raw format, but only in the forms of the neural correlate presented at the end of Chapter Three.

Figure 19 maps the neural correlates to the system time and to the experimental stimuli used in the Office-task experimental sub-phase. The horizontal axis represents

[1] 512 recordings per second, for 423+423+480 seconds over 8 EEG frequency bands, plus correlates, plus SpO2 and heart rate data for 61 participants.

system time. The zero coordinates marks the point in time when the sub-phase started (i.e. second zero), while the end of the graph (i.e. second 423) stands for the last second for which a neural correlate ratio is calculated. All randomized effects are rearranged to the default event order for the purposes of visualization and statistical analysis. Horizontal axis represents the value of the ratio behind the neural correlate. As explained in the previous chapter, the higher the value of the ratio is, the higher the effects of IO on the ECTs. The varying black line is the average value function of neural correlate over time. The boxed arrows (i.e. start, E1, E2 etc) and the corresponding shaded spaces mark the experimental stimuli and the duration of experimental stimuli respectively.

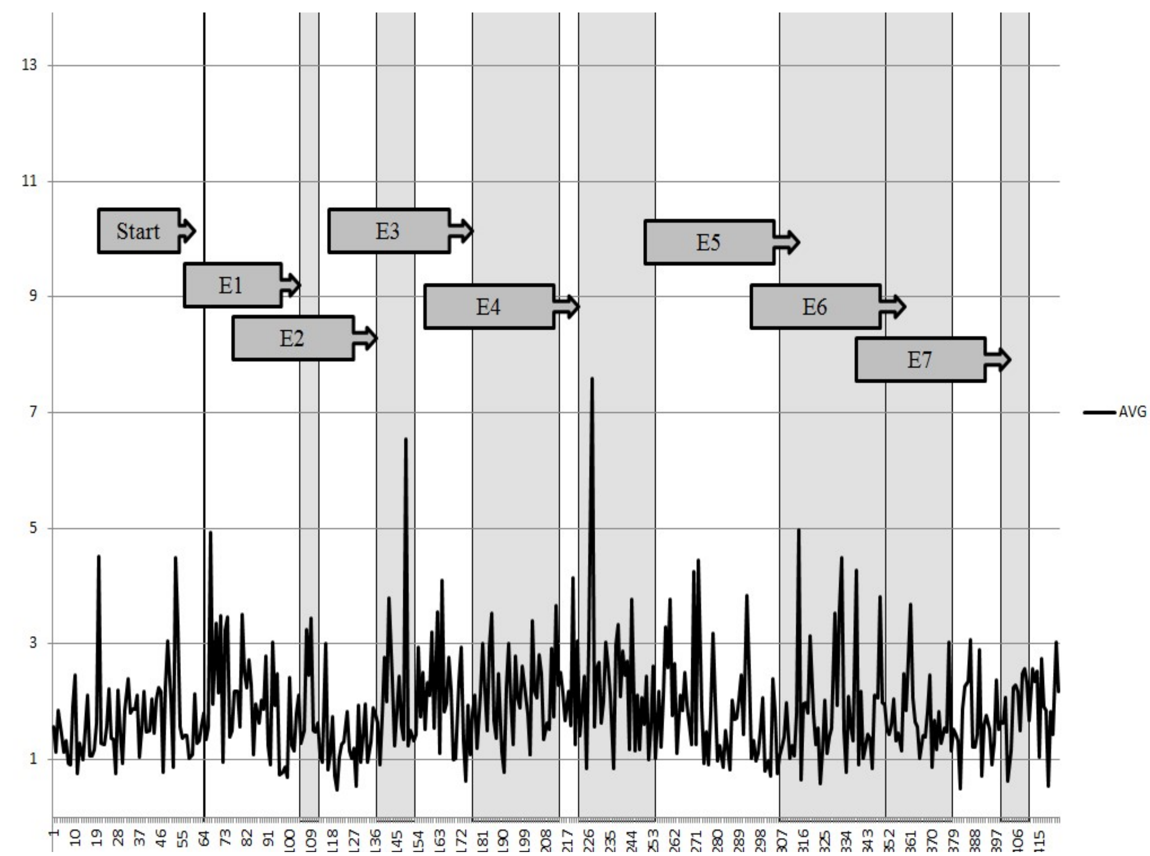


Figure 19: Data and Experimental Stimuli

The table below explains all significant events and stimuli which have created abnormally high correlate readings. All events were elicited, with an unexplained exception of E2.

Table 14: Events Specification

Event name	Explanation
Start	End of tutorial, start of the Office task.
E1	The first message sent to the participant by the system
E2	Unelicited spike present in 98.33% participants
E3	Skype textual message sent to the participant by the system
E4	First instance of “Wall of text”
E5	Skype voice message sent to the participant by the system
E6	Second instance of “Wall of text”
E7	Third instance of “Wall of text”

Figure 20 represents the value of the neural correlate for different groups. The average value for Digital Natives is presented at the top (AVGN), the average value for all participants (AVG) is in the middle, while the average value for Digital Migrants is presented at the bottom of the figure (AVGM).

Even before the formal statistical analysis of variance is conducted, it is clear that AVGN and AVGM have noticeably different values. Similarly, different instances that elicit IO also seem to provide a contrast compared to the pieces of data where only a regular II was elicited. For example, Event 3 (i.e. Skype textual message) testifies that

Digital Natives almost did not experience any correlate spikes during that epoch, while Digital Migrants experienced a very strong spike

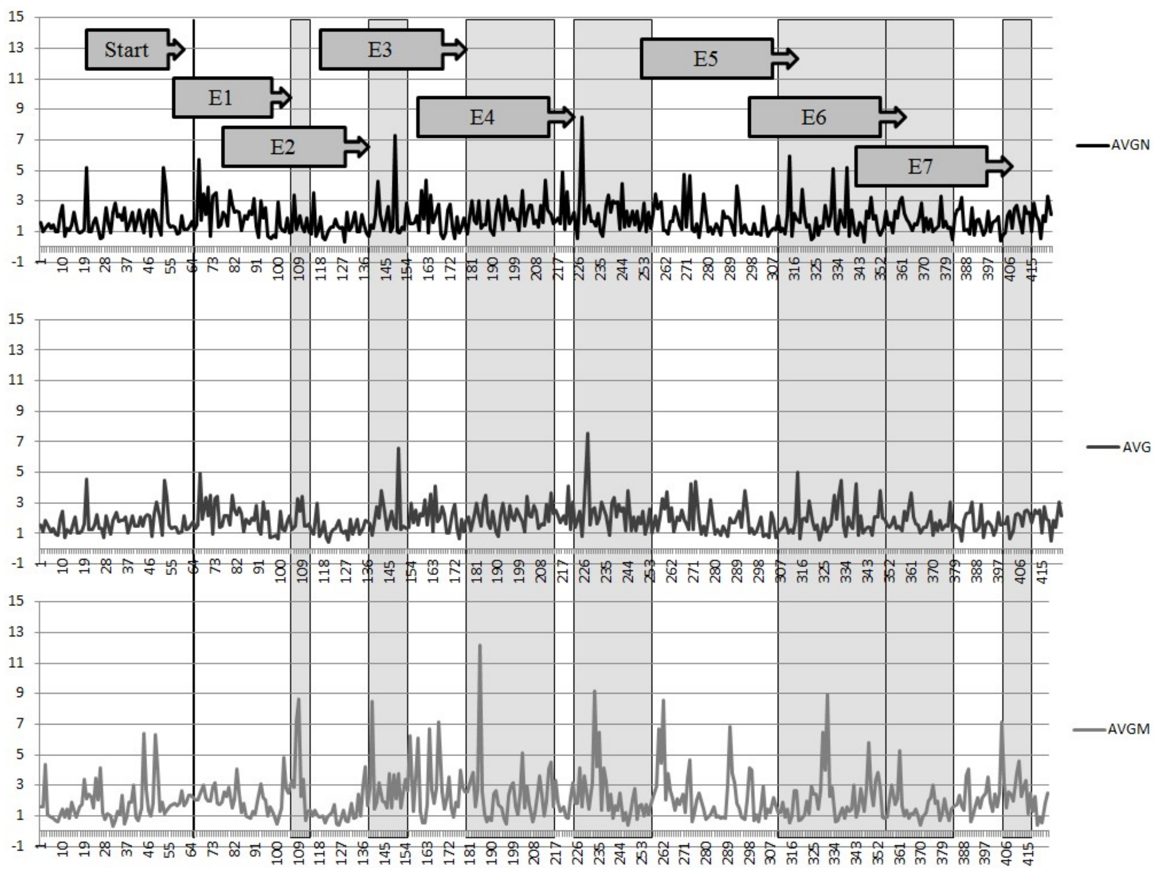


Figure 20: Readings for Natives, All Groups and Migrants

Figure 21 represents all minimal, average and maximal values of neural correlates over time plotted on an area chart. The black area stands for the highest value, the dark grey area marks average values, and the light gray area at the bottom stands for minimal values for each second. The system time dimension and the schedule of events are identical to the ones used in the previous figures. The smallest correlate value is 0.002, while the highest correlate value stands at 42.418. Interestingly, this value does not correspond to the point in time in which an IO stimulus is presented. It also does not correspond to the time events in which the eye movement could have polluted the signals. Even more surprisingly, this value is recorded on a Digital Native. This and similar outliers cannot be explained by the mechanism I present in Chapter Two of this dissertation and provide an intriguing exception to the general trends that can be seen so far in the collected data. I address these and similar exceptions in Chapter Five.

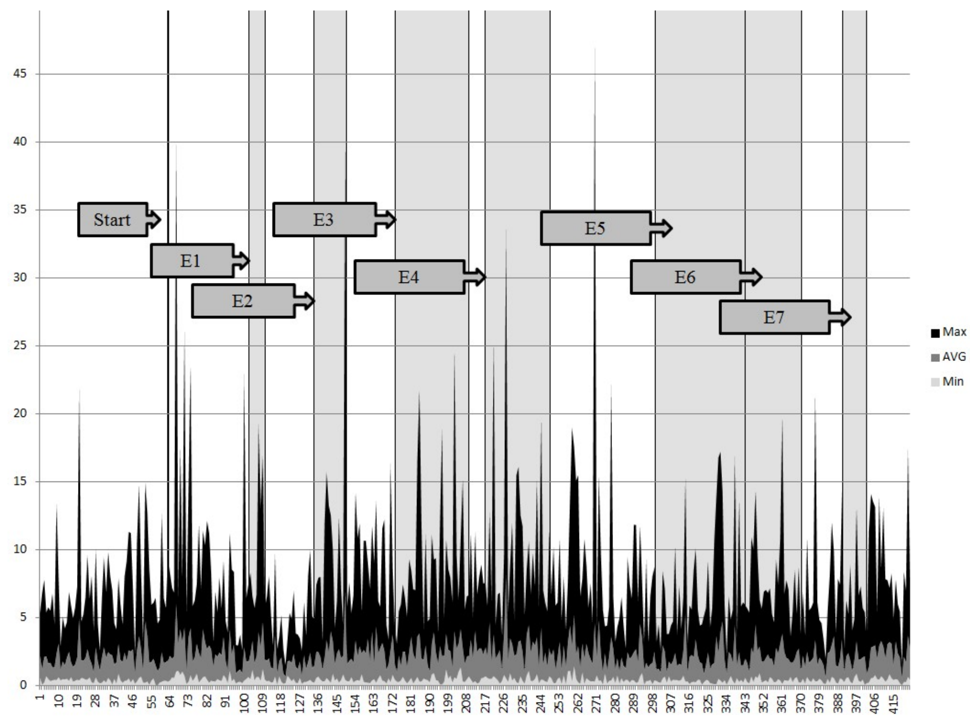


Figure 21: Overview of minimal, maximal and average values across the data

Validity

Validity is defined as an extent to which a set of measures truthfully represents the concept of the study, or as "the degree to which it is free from any systematic or nonrandom error" (Hair et al. 2010, p. 93). Establishing construct validity is more difficult in NeuroIS studies than in traditional quantitative IS studies. The problems begin with the actual conditions that can influence the neural readings. For example, the experimental environment in which neurophysiological tools are employed creates an artificial environment that limits the external validity of traditional neuro-cognitive studies. Furthermore, different neurophysiological tools are known to vary in their degree of artificiality (Dimoka et al. 2012). In short, this means that different experimental environments can produce different readings. Next, there remains the possibility of "mono-operationalization bias and construct validation concerns" (Dimoka et al. 2012, p. 682). Neurophysiological tools are often used to collect signals for only a single measure and for a given constructs. Thus, it is impossible to establish a straightforward methodology to assess the internal consistency of measures. It is also challenging to prove that the collected signals measure the neural correlate reliably (Cook 1979). Therefore, the measurement error beyond the simple signal clarity cannot be calculated because there is no way to filter the "true score" from the errors. In these situations, the only viable solution would be to conduct a series of retests with additional measurements of the same stimuli. This is impossible in many settings, including the experimental settings which I use in this dissertation. However, scholars do argue that even the data collected in this way still provides reasonable ground for sound statistical analysis (Straub et al. 2004). Consequently, assessing convergent validity would simply require multiple measures (i.e. Gefen et al. 2000) which are impossible to record in a mono-polar environment

Testing for Unanticipated Stressors

As explained in Chapter Three, I have measured participant's heart rate throughout the experiment. Research demonstrates that certain physiological conditions like anxiety and stress can pollute the EEG signals (Keil et al. 2014) in clinical settings.

To the best of my knowledge, it is still unknown if these or similar stimuli can pollute the CND recordings. Regardless, I use heart rate to control for potential unanticipated stressors. Heart rate variation is established as a sensitive and selective measure of stress (Hjortskov et al. 2004). To test for unanticipated stressor, I conducted analysis of variance of heart rate between different sub-phases and experimental stimuli. The analysis of variance failed to reject the null hypotheses, which means that significant difference in unanticipated stressor between IO and regular II states does not exist in this study. This further leads to the conclusion that significant stressors were not present in this experiment. The results of the analysis of heart rates and paper notes are presented in Appendix H.

Hypotheses Testing

Neuroscience employs sophisticated and untested statistical models to process the data coming from the clinical instruments. Relying on untested statistical methods with major software flaws seriously damaged the reputation of neuroscience as a discipline in a variety of ways. For example, fMRI-based methods have detected statistically significant brain activity inside the brain of a dead frozen fish obtained from a local supermarket (Bennett et al. 2009). Furthermore, Eklund et al. (2012) prove that parametric significance thresholds used to process neural data can both be very conservative and very liberal at the same time. This severely handicaps the ability to analyze neural data in a statistically rigorous manner. The newest blow comes from a statistical problem which renders thousands of neuroscience studies inaccurate to the level of being incorrect (Oxenham 2016). Although fMRI is more than 25 years old, not a single statistical method has been used to validate real fMRI data. Eklund et al. (2016)

used 499 controls to conduct 3 million task group analyses. Instead of finding 5% results of false positives, the statistical method used for processing fMRI data delivered false-positive rates of up to 70%. Thus, to avoid building this dissertation on unclear statistical grounds, I use a well tested parametric method which is suitable to test all hypotheses from Chapter Two (summarized below, Table 15) and which complements the experimental design and collected data.

Table 15: List of hypotheses

H. #	Text
H1a	Information Overload leads to strong Elementary Cognitive Task effects.
H1b	Information Influx does not lead to strong Elementary Cognitive Task effects until Information Overload is reached
H1c	Information Overload caused Elementary Cognitive Task effects endure even after the information influx is stopped
H1d	Information Overload leads to stronger Elementary Cognitive Task effects on Digital Natives compared to Digital Migrants.
H2a	Information overload is negatively related to the Information Richness of the information category
H2b	Information overload is negatively related with the media naturalness of the information category
H3	Consumer neural devices are capable of detecting specific IO related brain states using the constructs tested on clinical neural devices.

Parametric models are believed to offer “numerous benefits” in analyzing EEG data when compared to nonparametric approaches. The most important benefits are increases in robustness, reduction of noise, and volume conduction effects (Gordon et al. 2013). To analyze variance of parametric data in this study, I employ one-way analysis of variance (Fisher 1919) known as ANOVA. I use this statistical instrument whenever there is a need to detect if any statistically significant differences between the means of two or more independent groups exist.

ANOVA builds on the assumptions of independence of observations, data normality and homoscedasticity (Anderson et al. 2014). The independence of observations indicates that there is no relationship between the observations in each group or between the groups themselves (Kotz et al. 1988). The experimental design and the nature of the neural correlates I use guarantee that this assumption is fully met, especially since there are no known mechanisms in which EEG frequency bands influence each other. Assessing the normality, or the normal distribution of residuals, is generally conducted through the means of a standardized statistical test known as Shapiro-Wilk normality test. Unfortunately, this test cannot be used for my data set because it can only work up to 5000 samples (Rahman and Govindarajulu 1997). As stated in Chapter Three, my dataset contains 350 million observations in raw form, and around 25.8k samples in the neural correlate form. However, the data histogram and QQ plot for the neural correlated presented below (Figure 22) testify that the data coming from my experiment is normally distributed.

As there is a wide disparity in size between two groups in my data set, there is one practical issue to consider at this point. Unequal sample sizes are known to affect the homogeneity of variance assumption. Although ANOVA is robust to smaller departures from this assumption, a clear rule for assessing the point in which this can become a problem does not exist (Keppel and Wickens 2004). When the variance of the error terms appears constant over a range of predictor variables, the data is understood as homoscedastic. The assumption of equal variance of the population error is central to the proper application of many statistical techniques including ANOVA (Hair et al. 2010).

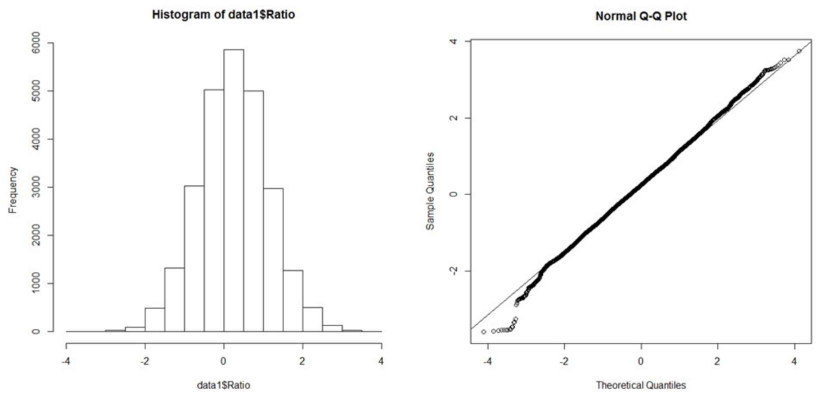


Figure 22: Normalized Data

The plot regression standardized residuals and neural correlate in this example (i.e. dependant variable) presented below demonstrates that the processed data collected from this experiment is almost perfectly homoscedastic (R^2=0.997). On these bases I conclude that all assumptions for using ANOVA are met.

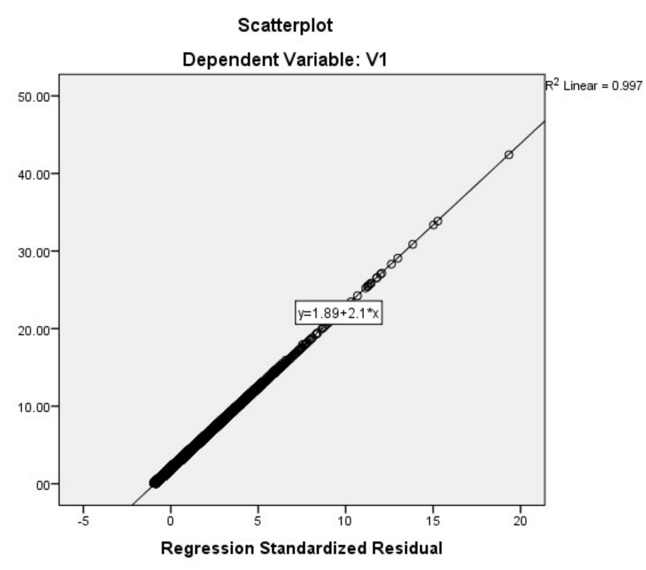


Figure 23: Data Homoscedasticity

The graphical representations, known as candlesticks, and presented in Figure 24, illustrate the basic properties of two groups of neural correlates. The first one, marked as OVER represents the readings during periods of time in which the IO was induced, while the readings marked as REG represent readings from the regular II. It can be clearly seen that IO does manifest with higher neural correlate readings when compared to the regular II, although regular II has stronger outliers.

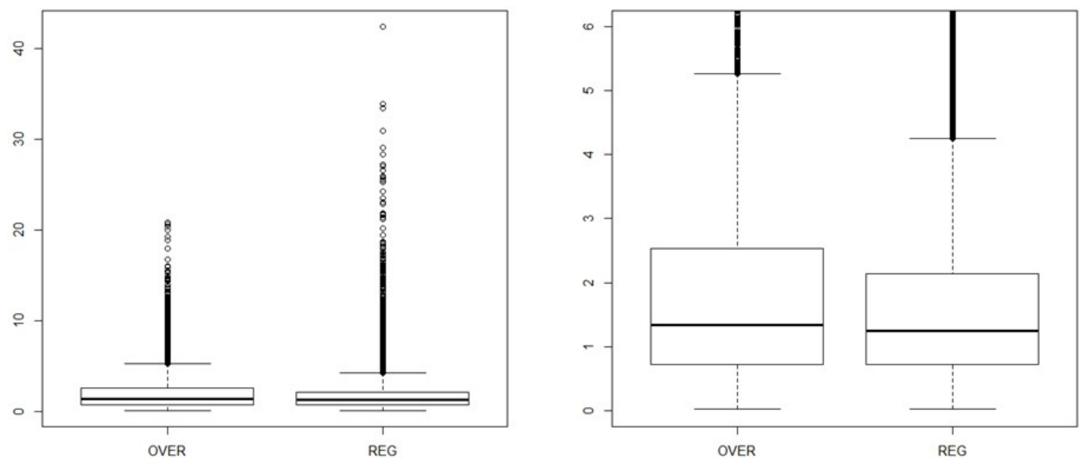


Figure 24: Candlestick representation of IO Overload and regular II groups

Furthermore, the independent between-groups ANOVA yielded a statistically significant effect, $F(1, 25.8k) = 17.72$, $p=0.0000000208$. Thus, the null hypothesis of no differences between the means of OVER and REG groups was rejected. This provides support for Hypotheses 1a and1b.

Hypothesis 1c states that Information Overload effects endure even after the information influx is stopped. To test this hypothesis, I group neural correlates in two groups: group one (AIO) contains all readings recorded after Information Overload stimuli, while group two (IO) is populated with readings during the information overload.

The illustrations below (Figure 25) show us that IO tends to have higher values of neural correlates, while the outliers are still slightly more pronounced in the AIO group.

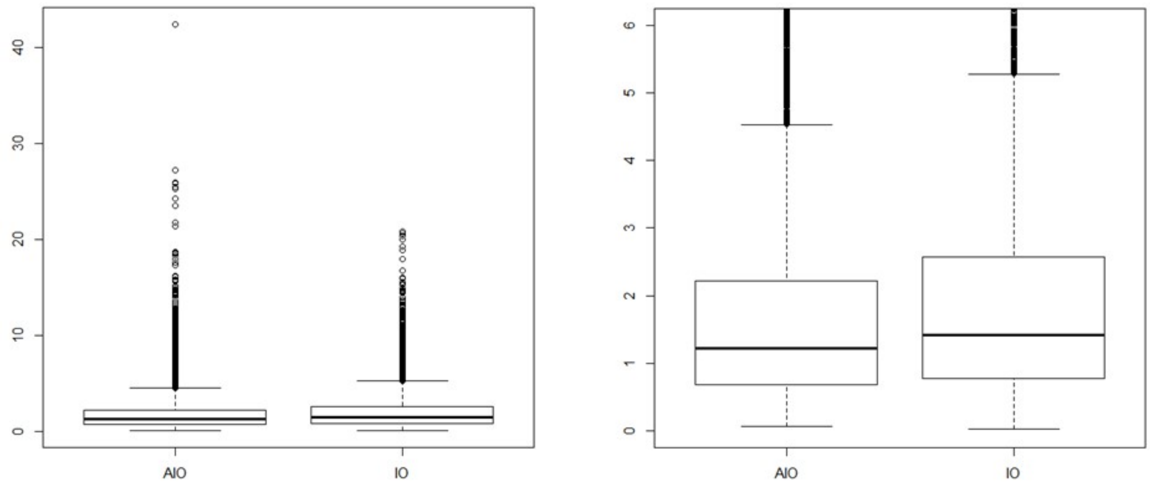


Figure 25: Candlestick representation of after IO and IO states

Next, the independent between-groups ANOVA resulted in a statistically significant effect, $F(1, 14.8k) = 9.515$, $p = 0.00204$. Thus, the null hypotheses of no differences between the means is rejected, lending support for Hypothesis 1c.

Hypothesis 1d posits that the effects of IO on ECT will manifest more strongly on Digital Migrants compared to Digital Natives. The data support this hypothesis since the neural correlate has higher average values in the Digital Migrants group than in the Digital Natives group, although the outliers presented below have higher value in the Digital Natives group (Figure 26). Once again, the analysis of variance presented below demonstrates that Digital Migrants and Digital Natives are two statistically different groups.

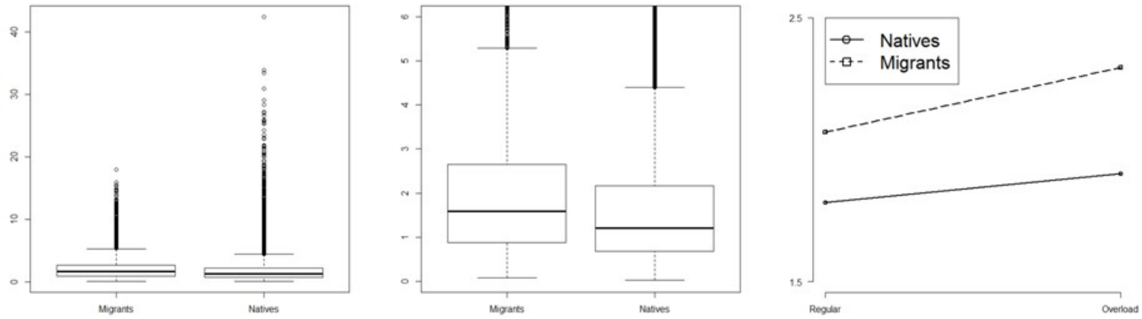


Figure 26: IO Differences between Digital Migrants and Digital Natives

Specifically, the independent between-groups ANOVA returned a statistically significant effect, $F(1, 25.8k) = 144.6$, $p = 2*10^{-16}$. Thus, the null hypothesis of no differences between these two groups is rejected. Combined, these results provide formal support for Hypothesis 1d.

Hypotheses 2a and 2b are designed to test if the postulates of IRT and INT respectively hold true in neural readings coming from the CND. The graphical representations of neural correlate readings and ratio means under different experimental stimuli are presented on figures 27, 28 and 29 respectively.

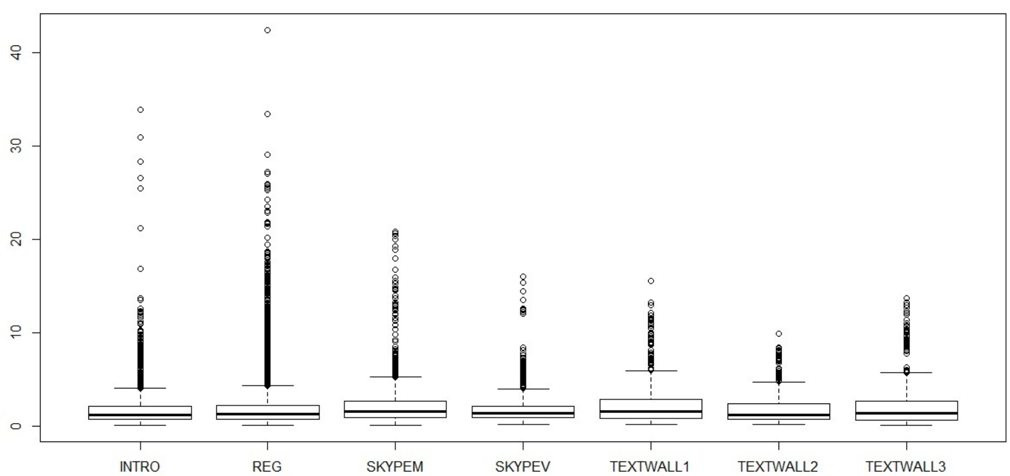


Figure 27: IO effects of different stimuli

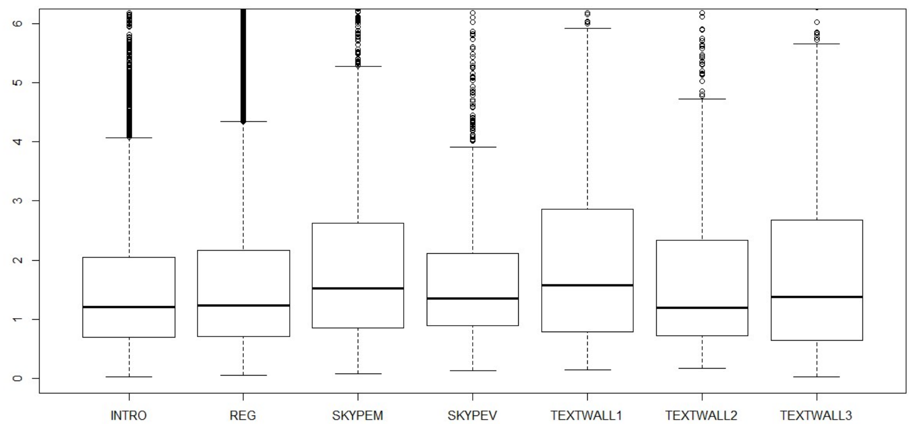


Figure 28: IO effects of different stimuli (trimmed)

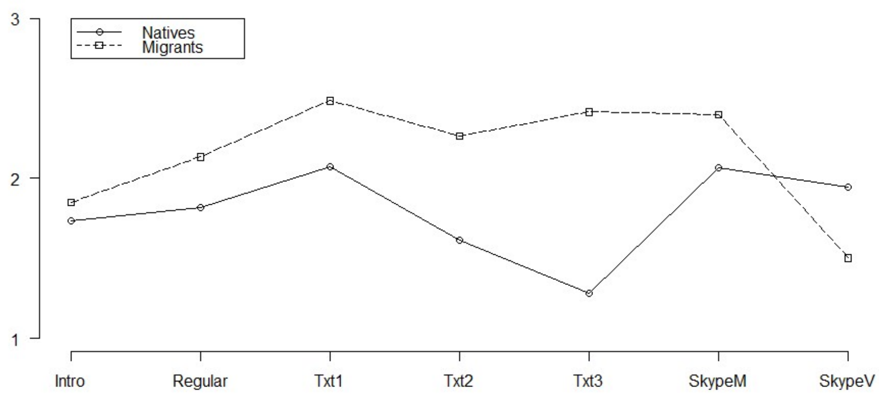


Figure 29: Average correlate values for different experimental stimuli

These illustrations show that voice, the most natural form of information used in this experiment, creates the smallest IO effects, while the highest IO effects come from the less natural forms, especially from text-heavy messages (TEXTWALL). These findings support INT postulates since the more natural information creates smaller IO effects than the less natural information – just as predicted by the theory. The IRT postulates are also working in neural correlates, especially since the fittest information sources for the task used for equivocal tasks did not record high IO effects. However, before I can explicate a formal conclusion, I must conduct an analysis of variance between these groups. The independent between-groups ANOVA yielded a statistically significant effect, $F(7, 25.8k) = 16.65$, $p = 2*10^{-16}$. Thus, the null hypothesis of no differences in ECT effects between different experimental stimuli means was rejected, which renders the stated groups statistically different. However, to formally assess which group pairs were significantly different at $p<0.01$, I conduct a post hoc Tukey's test and present the results below (Table 16).

Table 16: Tukey's test results

Items	diff	lwr	upr	p adj
REG-INTRO	0.0274	-0.0188	0.0736	0.6224
SKYPEM-INTRO	0.1931	0.1195	0.2666	0.0000
SKYPEV-INTRO	0.1229	0.0284	0.2174	0.0021
TEXTWALL1-INTRO	0.1844	0.1024	0.2664	0.0000
TEXTWALL2-INTRO	0.0072	-0.0899	0.1042	1.0000
TEXTWALL3-INTRO	0.0716	-0.0104	0.1536	0.1395
SKYPEM-REG	0.1657	0.1007	0.2307	0.0000
SKYPEV-REG	0.0955	0.0075	0.1835	0.0225
TEXTWALL1-REG	0.1570	0.0826	0.2314	0.0000
TEXTWALL2-REG	-0.0202	-0.1109	0.0705	0.9976
TEXTWALL3-REG	0.0442	-0.0302	0.1186	0.6200
SKYPEV-SKYPEM	-0.0702	-0.1752	0.0348	0.4641
TEXTWALL1-SKYPEM	-0.0087	-0.1025	0.0852	1.0000
TEXTWALL2-SKYPEM	-0.1859	-0.2932	-0.0786	0.0000
TEXTWALL3-SKYPEM	-0.1215	-0.2154	-0.0276	0.0022
TEXTWALL1-SKYPEV	0.0615	-0.0495	0.1725	0.7010
TEXTWALL2-SKYPEV	-0.1157	-0.2383	0.0068	0.0805
TEXTWALL3-SKYPEV	-0.0513	-0.1623	0.0597	0.8574
TEXTWALL2-TEXTWALL1	-0.1772	-0.2904	-0.0641	0.0001
TEXTWALL3-TEXTWALL1	-0.1128	-0.2134	-0.0122	0.0156
TEXTWALL3-TEXTWALL2	0.0644	-0.0488	0.1776	0.6709

The highlighted pairs were statistically different at a given alpha level (0.05), while the remainders of the group pairs were not statistically different. Thus, there is a significant difference in IO effects between Skype voice and textual messages and introductory messages, as well as with the first occurrence of text wall and introductory messages. Both Skype messages were statistically different when compared to the regular information influx, and so was the first instance of text wall. The second and third occurrence of text walls was also statistically different when compared to both Skype message types. Interestingly, the second and first occurrences of text walls are also proven to be statistically distinct when compared to the first occurrence of text walls. In general, these results partially support Hypothesis 2a, while also providing partial support for Hypothesis 2b. However, the situation here is not as unambiguous as it was in the previous hypotheses. This requires additional discussion which I present at the end of this chapter.

Finally, Hypothesis 3 posits that the Consumer Neural Devices are comparable to clinical instruments in detecting specific IO related brain states. To test this hypothesis, I compare the neural correlates gathered from the CND with the neural correlates of a clinical level study over comparable stimuli and at the identical EEG coordinates. If analysis of variance between these two sources demonstrates that the basic readings of an IO correlate coming from a clinical device are significantly different to CND supplied IO correlates, the Hypotheses 3 will be rejected. The reverse also holds true - if there is no statistically significant difference between the correlates coming from these two devices, the Hypotheses 3 will be supported.

To form the groups required for this analysis, I use the CND supplied data and the data from the corresponding EEG sensor from a publicly available EEG data recorded in similar environment. Specifically, I use the most rigorous and detailed publicly available dataset published on the official webpage of Swartz Center for Computational

Neuroscience[2]. I use Mathlab EEG lab to extract and process the signals from the clinical devices. According to the Swartz Center for Computational Neuroscience, Mathlab EEG lab is understood as the golden standard for analyzing clinical grade EEG data. Once I extracted the data from the clinical EEG device, I processed it in order to create the same type and quality of neural correlates I derived from the CND. The results of analysis of variance between these two data sets returned a statistically insignificant effect, $F(1, 421) = 1.02$, $p=0.313$. Thus, the null hypothesis of no differences between these two groups is supported. These results show that the difference between these two data sets is not statistically significant. And since the Hypothesis 3 states that Consumer Neural Devices should produce data similar to clinical neural devices, this lack of statistically significant difference between the CND and clinical EEG readings provides formal support for Hypothesis 3.

Results Discussion

Results of hypotheses testing are presented in the table below. Before I start with the discussion of results, I address the concerns of multiple comparisons. As it can be seen in the previous part of this chapter, the analysis of variance was conducted on a case by case basis. All separate analyses of variance resulted in very low p-values. This allows me to conclude, even under the umbrella of most conservative Šidák corrections of multiple comparisons (Sidak 1967), that the results of the analysis hold true even when combined.

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[2] The specific database I use is named "Psychophysics, various tasks (1Gb): more than 100 datasets available". I have downloaded it on April 15th 2016 from this link https://sccn.ucsd.edu/~arno/fam2data/publicly_available_EEG_data.html

Table 17: Hypotheses testing results

H.#	Text	Result
H1a	Information Overload leads to strong Elementary Cognitive Task effects.	Supported
H1b	Information Influx does not lead to strong Elementary Cognitive Task effects until Information Overload is reached	Supported
H1c	Information Overload caused Elementary Cognitive Task effects endure even after the information influx is stopped	Partially rejected
H1d	Information Overload leads to stronger Elementary Cognitive Task effects on Digital Migrants compared to Digital Natives.	Supported
H2a	Information Overload is negatively related to the Information Richness of the information category	Partially supported
H2b	Information Overload is negatively related with the media naturalness of the information category	Supported
H3	Consumer neural devices are capable of detecting specific IO related brain states using the constructs tested on clinical neural devices.	Conditionally supported

Hypotheses 1a and 1b are supported in a very clear and strong manner. This means that IO indeed creates strong ECT effects – but only when II influx accompanied with information excess moves to the IO levels. On these grounds, it is possible to conclude that, in general, the effects of IO are indeed stronger and thus detrimental to individual performance. Hypothesis 1c was partially rejected since the effects of IO on ECTs performance were not as strong after the IO as they were during the IO. These results allow me to conclude that IO effects are tied to the actual duration of the heightened II, and that the strong effects on ECT performances do diminish as soon as II is returned to normal. However, although these effects diminish, the neural correlate still remains higher than during the regular II. Hypotheses 1d is supported since the extent to which Digital Migrants experience IO is stronger compared to Digital Natives. These findings should be treated as a warning. According to the experimental results, it seems that the migrant generations, who are still likely employed in their peek potential, suffer from IO more than the generations which are yet to dominate the workforce. In short, it seems that the hardest effects of IO are yet to come. Combined with the ever-growing amount of information, this paints a rather worrying picture. To make it worse, Digital Natives experienced higher IO during the Skype Voice message than their Migrant counterparts. This will probably render the generation change problematic, since the verbal instructions coming from Digital Migrants to Digital Natives might amplify the IO in Digital Natives instead of helping them to understand the messages (i.e. advices and instructions) coming from Digital Migrants. In summary, the hypotheses from group one tells us that IO creates strong ECT effects. These effects are not manifested during the normal II unless it is accompanied by information excess, and these effects do not last after the II is returned to normal conditions. Furthermore, in tune with the theoretical mechanism used for this dissertation, the Migrant generations seems to experience IO harder than Digital Natives. The only exception to this situation is verbal II.

Results of Hypotheses 2a and 2b provide grounds to assess if IRT and INT respectively work inside the human brain and in the ways which can be measured by the CND I use for this dissertation. The premises of IRT were supported. This tells us that, assuming task fitness, the richer communication channels can amplify IO overload, rather than to diminish its effects – as initially theorized by Daft and Lengel. Similarly, INT postulates were proven to be correct, since the more natural information does provide smaller (if any) ECT effects compared to non natural information. Another interesting finding comes from analyzing the differences in IO coming from series of Text Wall stimuli. Specifically, the results show that the IO is the strongest during the first stimuli. Finally, conditional confirmation of Hypothesis 3 furthers the basis on which future NeuroIS studies can use CNDs to study IO – especially since a clinical device provided similar results to the results coming from the CND under the assumptions that the data processing did not distort the data set coming from the clinical device.

CHAPTER FIVE

Discussion

In this final chapter of my dissertation, I build on the findings of the data analysis and discuss a set of implications, limitations, directions for future research and conclusions. I pay particular attention to theoretical, practical and methodological implications. This chapter also presents all the limitations of this dissertation in a separate sub-chapter. I believe this dissertation provides a solid ground for future IO and CND research. With that in mind, I also discuss the directions for future research endeavors. Finally, I end this chapter with a concise conclusion about my findings. This chapter mostly builds on the data analysis conducted in Chapter Four, although I also reflect on methodological basis from Chapter Three, as well as on theoretical and literature foundations from earlier chapters.

Implications

This dissertation has the potential to create wide-ranging implications for both academic and practitioners' community. One practical consequence includes the use of CNDs to detect IO in "real world" and outside-the-lab environments. Furthermore, theoretical ramifications build the theoretical mechanism of information overload, while also providing the basis for creating a new theory for understanding how digital information influences ECTs. Additionally, the methodological implications of my research cover the changes in methodology I develop to facilitate the experiment on which I base this dissertation. Finally, the managerial and organizational implications are designed to sum the findings of this study in a way that is fitting for augmenting the established managerial practices and organizational traditions.

Theoretical Implications

This chapter starts with a set of theoretical implications. To begin with, the neural readings I collected from the CND enable us to understand how Information Richness and Information Naturalness theories work inside the human brain. The conditional support for H2a, which states that IO is negatively related to the Information Richness of the information category, tells us that the IRT is grounded in the human brain given that task fit assumption is adequately set. In particular, rich media did reduce the effects of Information Overload, while the media-to-task fit reduces the effects of Information Overload in some instances (i.e. voice message) and amplified in others (i.e. Skype message). For example, Raman et al. (1993) advocate that groups using a communication medium that is too lean for their task end up experiencing more difficulties compared to groups with a communication medium that is too rich for their task. My neural readings echo their findings, since multiple neural measurements show that information rich messages (i.e. Skype voice stimuli) caused smaller levels of IOs. Other aspect of IRT also hold true in my neural readings. The information which was fitting for the task in terms of richness (i.e. regular information influx) did not cause IO. Similarly, electronic message richness, and the corresponding neural correlates, were also proven to vary across individuals, just as Schmitz and Fulk (1991) posit. Furthermore, some later works based on the IRT (i.e. Carlson and Zmud 1994, 1999) were also proven to hold true in the neural correlates I have collected. Specifically, different experiences with the communication channels did cause statistically significant differences between the

Digital Natives and Digital Migrants just as Hypothesis 1d posits. Thus, it seems that the core concept of IRT, which argues for fitting the media richness with the communication task, holds true for textual information influx inside the experimentally simulated system, and fails when the information is being transmitted outside the system (e.g. via Skype) or in more natural channels. Thus, my findings also testify that IRT is neither universally right (as implied by Daft and Lengel, 1986) not universally wrong (as claimed by Cook, 2004). Core postulates of Information Naturalness Theory were mostly supported by the neural readings. Specifically, the hypothesis H2b stating that Information Overload is negatively related with the media naturalness of the information category was confirmed. This demonstrates that the core premise of this theory, which claims that the more natural the form of communication, the more efficient the information dissemination should be, is supported by the neural readings.

In short, these theoretical implications demonstrate that both IRT and INT should be integrated to provide an overarching theory capable of explaining the congruency of digital information required for optimal processing of information influx by the human brain. I believe that the Theoretical Mechanism of Information Overload can be a good starting point for creating that overarching IO theory. This is especially true since the multiple constituent statements of relationships from the Theoretical Mechanism of Information Overload were supported by the data I collected. On a similar note, all theoretical constructs and causal mechanisms of the said mechanism were also present in the data. The only part of the mechanism that did not work as I have theorized is the one presented in the statement of relationship 2. This part of the mechanism posits that strong ECT effects are present even after the intensity of information influx returns to normal levels. The reasons behind the failure of that specific part of the theoretical framework are unknown and that creates yet another theoretical implication that should be addressed in future IO theorizing attempts.

Methodological Implications

The methodological implications of this dissertation are twofold. Firstly, this study builds the methodological base on which further CND studies can be conducted. In Chapter Three, I provide a set of experimental procedures which detail the way in which the future research could approach CND experimentation in real-world environments. Secondly, I provide a neural correlate which was able to use the existing neural measures in a CND environment with a low spatial resolution and still provide usable results. This methodological approach allows future researchers to use exactly the same concept I have used, or to explore other constructs which can potentially work in similar settings.

Practical Implications

Instead of relying on clinical instruments, this study uses an inexpensive plug-and-play Consumer Neural Device. Furthermore, this study uses a consumer device in an office environment that is more common in standard IS scenarios than a laboratory environment. All data points from the device are collected and stored in real time. Combined, these characteristics position the results of my dissertation very closely to potential practitioners because it allows an inexpensive real-time and real-world way of measuring a set of important brain activity parameters. This approach empowers all information-heavy organizations to inexpensively increase the welfare and productivity of their knowledge workers by using the neural readings. The same approach also enables them to gather the neural readings to potentially allocate resource heavy tasks to the employees who are experiencing the lowest levels of Information Overload. My dissertation also provides ground for improving the contemporary information systems based on the neural feedback. In other words, the system developers and other software-centric practitioners can use the process I describe throughout this dissertation to better understand how their users process the information coming from their systems. Specifically, I argue for paying the special attention to using the identical media formats throughout the system (i.e. using solely textual information instead of combining textual and voice messages). Furthermore, practitioners can also use the results from the previous chapter to redesign the manner in which their information systems disseminate the information to their employees. For example, it seems that information is disseminated best if only one information systems is used for information dissemination. Therefore, practitioners should focus on developing systems that can encompass multiple information sources and forms under one GUI. The practitioners can also use the NEx software data buffers and CND APIs explained in the Appendices to develop a real time application for monitoring IO levels. This can be helpful since the future software could be equipped with algorithms that detect information overloads and potentially decrease the information influx for the overloaded individuals.

This project also enables organizations to efficiently and affordably detect and potentially prevent information overloads among its employees in real time. Although some organizations like the US AirForce use EEG based devices to monitor the performances of their members (i.e. pilots), since 1970s the technical properties of these devices (i.e. lack of ergonomic properties) have limited their applicability in office environments. With the introduction of compact mono-polar CNDs, organizations can conveniently monitor neural parameters for the key employees and thus improve their overall wellbeing and performances. And, as CNDs get closer to average consumers (i.e. Elon Musk's Neural Lace project), having an active CND installed on all employees might become as common as having them equipped with mobile phones or FitBits. The findings from Chapter Four also inform the managers about cognitive effects coming from different ways of communicating. In particular, switching from one form of communication to another generally results in strong cognitive effects. Similarly, Digital Natives exercise greater cognitive efforts when processing voice messages, while Digital Migrants struggle with all other forms of communication.

Overall, concise textual information works best for simple tasks. However, to avoid unnecessary IO effects, managers should restrain from using multiple systems to transfer the information to their peers and subordinates. Furthermore, managers should also note that Digital Migrants and Digital Natives process different types of messages in a different manner. According to my findings, short voice messages are best suited for Digital Migrants, while Digital Natives seems to be responding best to short textual messages. Next, Digital Natives do appear to be overloaded more to a series of dense textual messages, while the Migrants prove to be better suited in handling these messages. All these findings allow the managers to alter their communication routines and potentially fine tune organizational structures to better accommodate overload-free work environments. Achieving overload-free environment could be important for managers, since the entire body of literature I present in Chapter Two - sub-chapter about

Information Overload effects, states that Information Overload amplifies stress and ultimately reduces the productivity on both individual and organizational levels.

Data from the Consumer Neural Devices also constitutes a rich, objective, real time and real-world data source. As such, this data source can give businesses noticeable competitive advantages in multiple areas. For example, my study can be used to fine tune the information influx by implementing software algorithms to control for Information Overloads. This can prevent IO from influencing the performances of decision support systems and decision makers. Same holds for creating overload-free briefings, reports and presentations. Furthermore, rich neural data can also help businesses better understand how their consumer react to any information intense product – be it a digital magazine, a specific piece of software, computerized accessories, home appliances, car infotaiment systems, consumer electronics or any other information rich product.

Limitations

This dissertation is not without limitations. Most of the limitations come from the technical characteristics of the CND I use. The biggest limitation comes from the mono-polar EEG environment. This limits the potential to gather data from all EEG locations that are known to manifest during a specific stimuli. Furthermore, the small number of electrode locations and the resulting low spatial resolution prevents me in entirety to use neural correlates that require EEG readings beyond FP1 and AP positions. Thus, some high-resolution neural correlates that might be capable of augmenting the understanding of IO are left out. These correlates are, for example, P200 readings that show cognitive matching, detection of target stimuli, selective attention, feature detection (Philips & Takeda, 2009), N200 which demonstrates detection of a deviation of a concrete stimulus from an expectation, automatic novelty-sensing, hedonic preferences (Folstein & Van Petten 2008, Handy et al. 2008), left-frontal-asymmetry and right-frontal-asymmetry (Wheeler et al. 1993). Luckily for future CND research, almost all CND manufacturers are either developing or announcing the development of the next generation of CNDs with significantly higher spatial resolutions. This should empower the future researchers to use a wider spectrum of neural correlates and to expand the CND research well beyond the IO domains.

The second technical limitation comes from the sheer novelty of the instrument I used to collect the data. To begin with, it is absolutely certain that the neural readings are influenced by experimental stimuli that are supposed to influence the readings (i.e. different levels of information influx). The same holds for the readings which come from a physiological activity which was not experimentally induced (i.e. blinking). Thus it is very clear that the data coming from this device is not likely to produce false positives comparable to brain activity in a dead salmon (Crowley et al. 2010; Katona et al. 2014; Yoh et al. 2010). However, the data I collected does have a non-negligible number of outliers. This demonstrates that CNDs are still limited when it comes to the data clarity caused by extraneous factors like electrical elevators, lightning systems (i.e. Harmon-Jones & Beer 2012) or high stress levels (Tams 2014). The third and final technical limitation stem from the fact that consumer neuroscience research is a compilation of only loosely related subjects (Plassmann et al. 2007) and as such is still not capable of following the rigorous standards of neuroscience fully.

Other limitations come from non-technical factors, like sample size and stimuli design. Although the sample of 61 participants is well above the samples used in similar

EEG studies, it is still possible to argue that the greater and more diverse sample could have expanded the generalizability of the findings. Moreover, the population used for this experiment is heavily skewed towards the Digital Natives, despite my best efforts to recruit similar numbers of Digital Natives and Digital Migrants. The design of the TEXTWALL stimuli could also mean that task-irrelevant information produces Information Overload and not just the property of the medium. Finally, this dissertation relies on measuring neural data created during a series of simple cognitive tasks. Although it is possible to speculate that the human brain might perform similarly in more challenging conditions, it is impossible to extend the speculation into more substantial conclusions without proper testing.

Directions for Future Research

This dissertation provides multiple directions for future research. To begin with, it opens the door of CNDs to investigate real-world IS phenomena that were previously impossible to investigate outside the clinical settings. My dissertation also sets the scene for CND based investigations of real-time phenomena. I hope that this study can motivate IS researchers to collaborate with neuroscientists in order to create a systematic representation of constructs and scenarios that can be measured by using only CNDs or clinical equipment and to seek for the constructs and scenarios which could be measured by both classes of devices. This can allow IS researchers to vastly expand the usage of CND and to create a process to systematically compare performances of the upcoming CNDs with the performances of their clinical counterparts. If conducted properly, I believe that this future research can gradually allow consumer NeuroIS studies to follow the standards set by the neuroscience. Similarly, future studies could explore triangulating objective and quantifiable data coming from CNDs with qualitative sources (Milic 2016). And since it is known that cultural values play “a common role in determining patterns of IT development, adoption, use, and outcomes” (Leidner and Kayworth 2006) future research can also use CNDs to understand if different cultures experience information overloads in similar manners. Finally, triangulating the quantitative neural data with qualitative data could allow us to deepen the understanding of differences between unconscious and conscious human reactions when it comes to using information systems or information intense products in general.

Conclusion

To conclude, this dissertation paired a novel CND with established concepts from the neuroscience to explain the mechanisms of Information Overload on an individual level. I have conducted an experiment on 61 participants and used the data collected from the device to test the theoretical mechanism of IO presented in Chapter Two. According to the results of my analysis, Information Overload leads to strong elementary cognitive task effects while the regular levels of information influx do not. Some effects of Information Overload are present after the information influx is stopped, however these effects are very small. Information Overload seems to have a stronger effect on Digital Migrants than on Digital Natives. Furthermore, Information Overload seems to be negatively related to the naturalness of the information, while Information Richness works in a more nuanced fashion. Finally, comparing the variance between the largest and the most detailed publicly available EEG dataset has proven that CND can indeed produce results comparable to the results produced by the clinical equipment at least when neural reading used to measure Information Overload are concerned.

APPENDICES

APPENDIX A

Consumer Neural Device – Technical Details

This research uses Neurosky Mindwave, a Consumer Neural Device marketed to wider audience. This CND uses a clustered dry electrode which is easy to mount on user's forehead and which eliminates the need to use any form of conductor gels to establish effective data stream. According to manufacturer's specification, this device has the following characteristics:

- 30mW rate power; 50mW max power
- 2.420 - 2.471GHz RF frequency
- 6dBm RF max power
- 250kbit/s RF data rate
- 10m RF range
- 5% packet loss of bytes via wireless
- UART Baud rate: 57,600 Baud
- 1mV pk-pk EEG maximum signal input range
- 3Hz – 100Hz hardware filter range
- 12 bits ADC resolution
- 512Hz sampling rate
- 1Hz eSense calculation rate
- Dry electrode
- Mono-polar configuration

This device uses ThinkGear Connector software to communicate with host's operating systems. Raw data is not accessible from the manufacturer's software and the manufacturer refuses to provide the algorithm which is used to calculate different neural cognitive performances (e.g. concentration and meditation). That is why this dissertation employs a tested third party open source solution (Neuro Experimenter - NEx) to access the device's API and to record the data stream in its raw format. NEx has a produced a proven set of replicable studies (Mellender 2016).

APPENDIX B

Experimental Software - Neuro Experimenter

This program (NEx) provides an interface to Neurosky Mindwave hardware (Mellender 2016). This program was originally developed for Neurosky Mobile and repurposed for Neurosky Mindwave in order to provide raw data streams for this dissertation. Thus, I hereby clarify that NEx is not my work, but a repurposed work of a dedicated individual. A Neurosky headset used for this study was purchased from Amazon. The official list of Neurosky devices that are expected to work with NEx are the following:

- MindWave Mobile (Black headset, tested with NEx)
- MindWave (White headset)
- MindBand ThinkCap
- TGAM module TGAT ASIC

Neurosky MindWave comes with manufacturer's drivers. Those drivers are compiled together in form of a ThinkGear connector software package. This software package is problematic because it does not allow raw signals to be captured. It is impossible to use the data stream coming from the device unless it is possible to trust fully that the values ThinkGear supplies are correct and representative of real EEG readings. Blindly trusting values from the manufacturer who denies disclosing the way in which those values are calculated is unacceptable for any scientific study. That is why this dissertation uses NEx application to access the raw signals from the CND sensors.

NEx application is extremely useful because it does not require ThinkGear connector to be active while the experimental is conducted. NEx however requires the system user (i.e. experimenter) to update systems drivers to the newest (as of spring 2016) system drivers. This is necessary to ensure optional functioning of the hardware inside the CND. NEx application is designed to run exclusively under Windows systems. Author provides detail description about system test performances on Windows 7 (Mellender 2016) and speculates that Windows 10 operating systems should also support NEx application. However, the tests I have conducted prove that NEx is not performing optimally on Windows 10, because COM ports failed to detect the CND inside the NEx environment multiple times. That is why I have collected all data for this dissertation using NEx on Windows 7 machines. NEx cannot be used without having at least .NET Framework 4.5 installed on the machine. According to Mellender (2016) notes, NEx is under constant development and it might be possible that by the time this dissertation is completed or published the aforementioned problems are fixed. As it creator states, the main function of NEx Is to collect brainwave readings from the Neurosky CNDs. NEx also has the functions which allow the experimenter to explore different "mind states" as defined by the manufacturer (i.g. meditation, relaxation and concentration). Moreover, NEx also has the option to combine different brainwaves to create a particular construct (e.g. as seen in Müller-Putz et al. 2015).

NEx is freely accessible for download either through the Neurosky mind app store or directly from its creator's website. At the time when this dissertation was written, NEx software package was available free of charge. Furthermore, NEx is a light weight software solution. Its installation will not update the system registry or any other system or user files outside of the installation folder. The only exception occurred when NEx stored its settings and exported logs. This software allows its users to use it in “emulation mode”. Emulation mode serves as a simulation of the actual data stream recording from the CND, however all the data points are randomly generated. According to its creator, the emulator mode is designed to provide a safe training environment for new users. Emulator mode does not require a CND to be connected to the system.

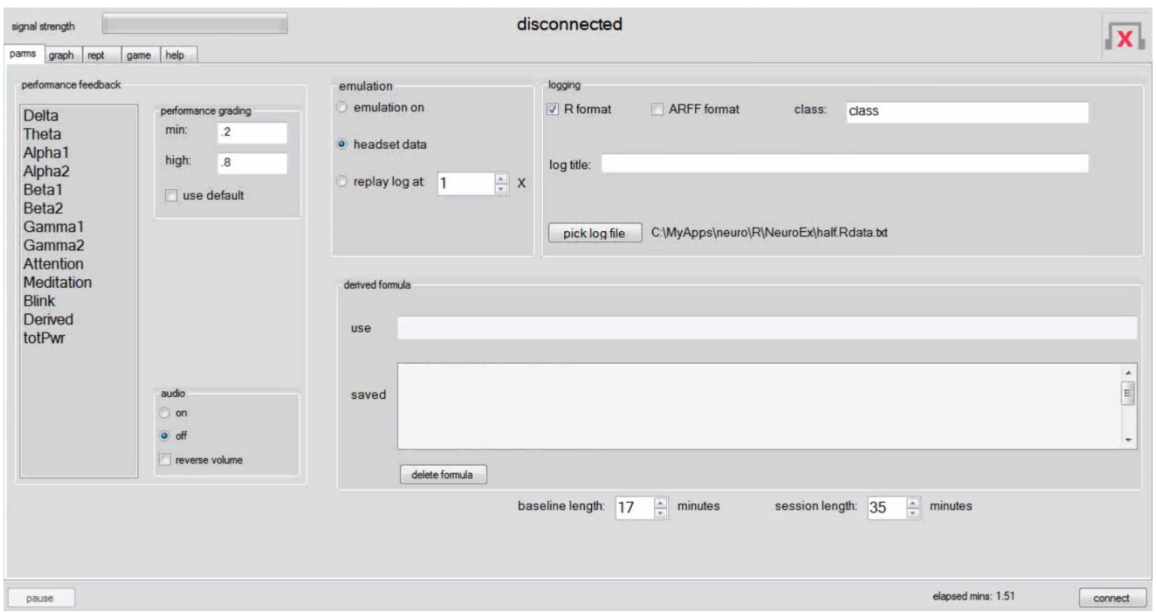


Figure B.1 : NEx Graphical User Interface

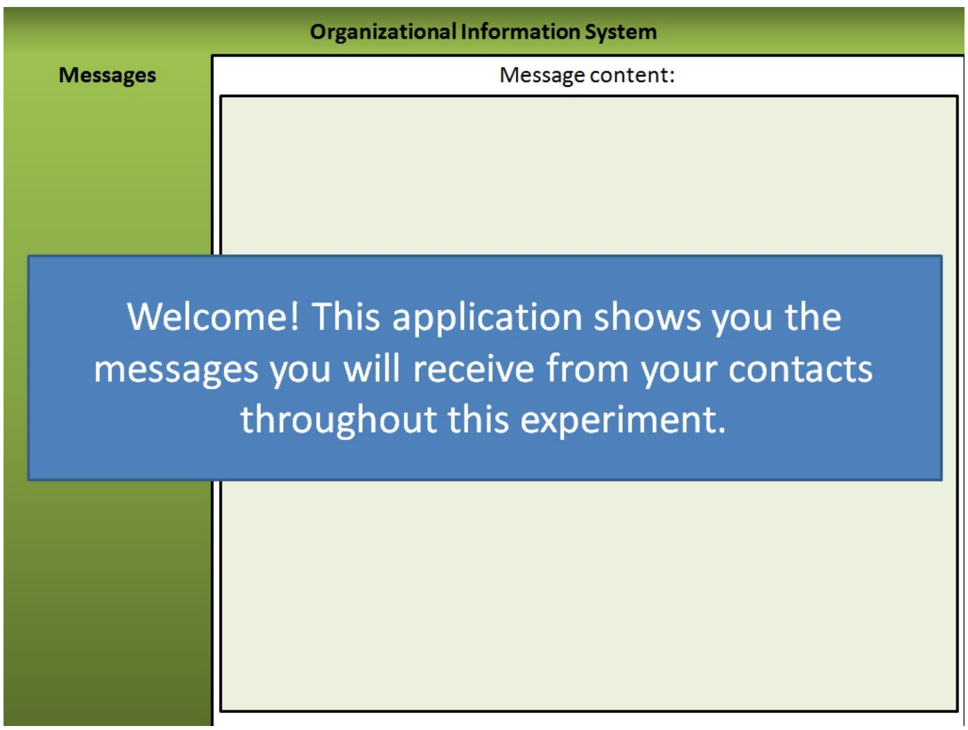
To run NEx user has to complete a set of steps. Firstly, user needs to verify that the headset can connect to the machine which is used for recording EEG readings. In other words, NEx has to have an active connection through one of the common communication ports. The default port for communicating with the device is set to COM5. NEx has a support search application which can test if the device is connected to the system using different ports. Secondly, it is imperative to make sure that no other neuro application is active because CND's API cannot reliably supply the data stream to multiple applications at the same time. When those steps are completed, NEx can be activated to record the EEF signals from the device. Performance feedback section of NEx's GUI allows user to select which reading should be recorded and/or displayed. At the moment of dissertation writing, NEx supported the following EEG band waves: Delta, Theta, Alpha 1, Alpha 2, Beta 1, Beta 2, Gamma 1 and Gamma 2. Alpha 1 and Alpha 2 data streams correspond to high and low Alpha bands respectively. Same logic applies to Beta and Gamma bands. In addition to EEG band waves, NEx also records data points for ocular eye movements (Blink) and total power (totPWR) which are used to control for outliers and to render readings under different power levels comparable. Finally, NEx can also record the values of Attention and Meditation parameters. According to the device manufacturer those parameters are calculated based on a set of patent algorithms. Up to the point of writing this dissertation, the device manufacturer did not provide a clear and unambiguous definition of those two parameters nor did it supply the algorithms behind its calculation. For those reasons, Attention and Mediation are impossible to link with any existing scientific studies. Thus, those two parameters were not used in my dissertation.

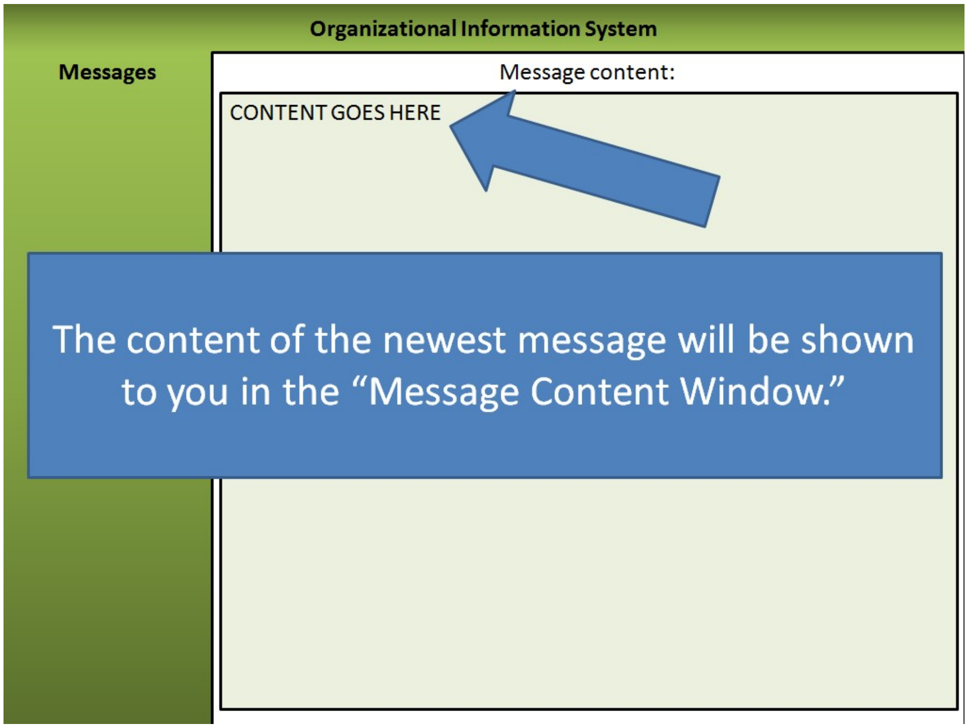
NEx documentation provides a detailed description of the experiment which was conducted by the NEx creator to test if this software solution is actually accessing the CNDs API and to document the corresponding results. Experiment uses NEx to test if the data streams from the device can record the difference between two extreme brain states: meditation and ordinary mind states. Experiment was run on a set of volunteers with more than 20 years of experience in meditation. The experimental session was divided into 2 parts. First part, the baseline recording, had the length of 17 minutes. Activities used for the baseline recordings are the following: internet browsing and reading. The second part, where the meditation occurs, had the length of 17 minutes. Approximate break between those two experimental phases was a1 minute. After the meditation phase was completed, data points were exported into an R-compatible database.

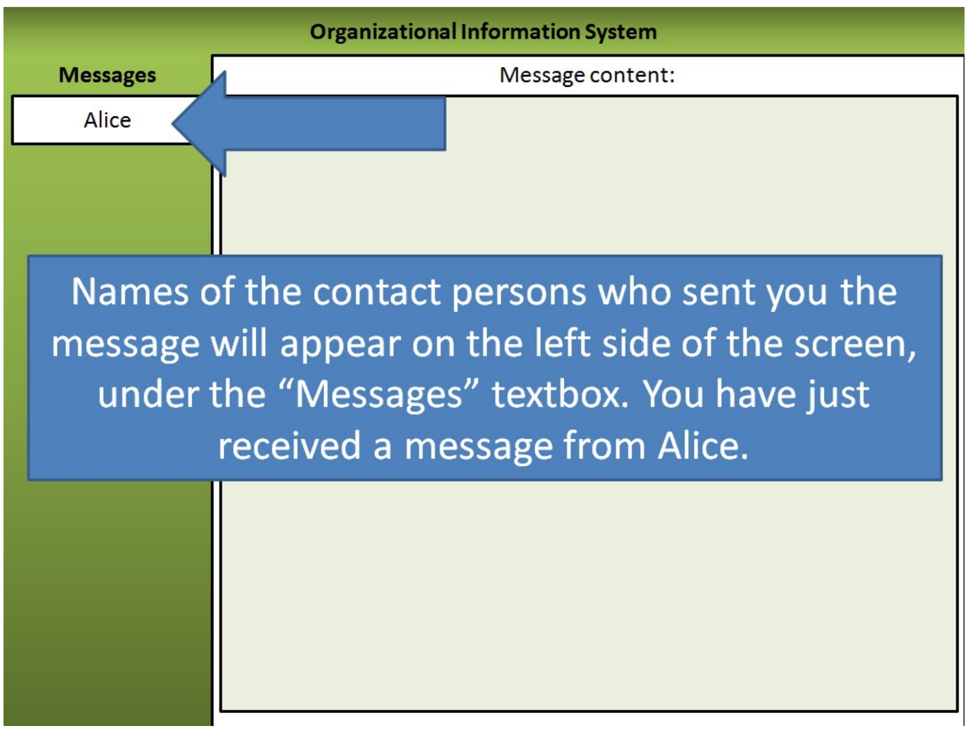
APPENDIX C

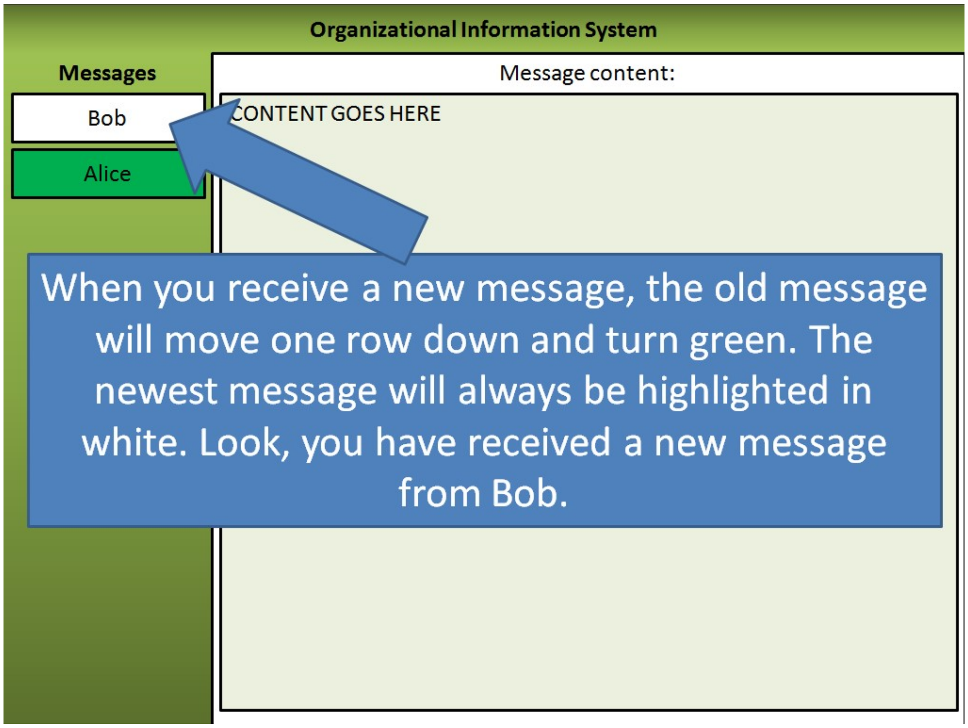
Experimental Software Interface

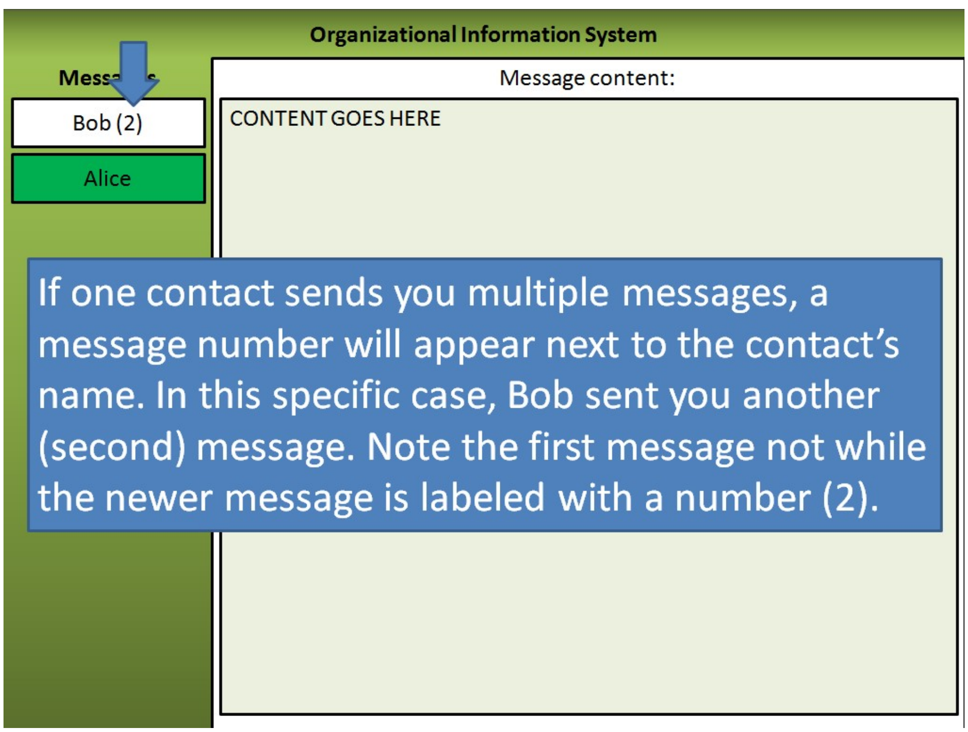
The screens below show a potential combination of messages as they would appear in the Experimental Software Interface. Please note that the content of the tutorial section did not change, while the letter parts of the experiment did change in order to mitigate potential order effects.

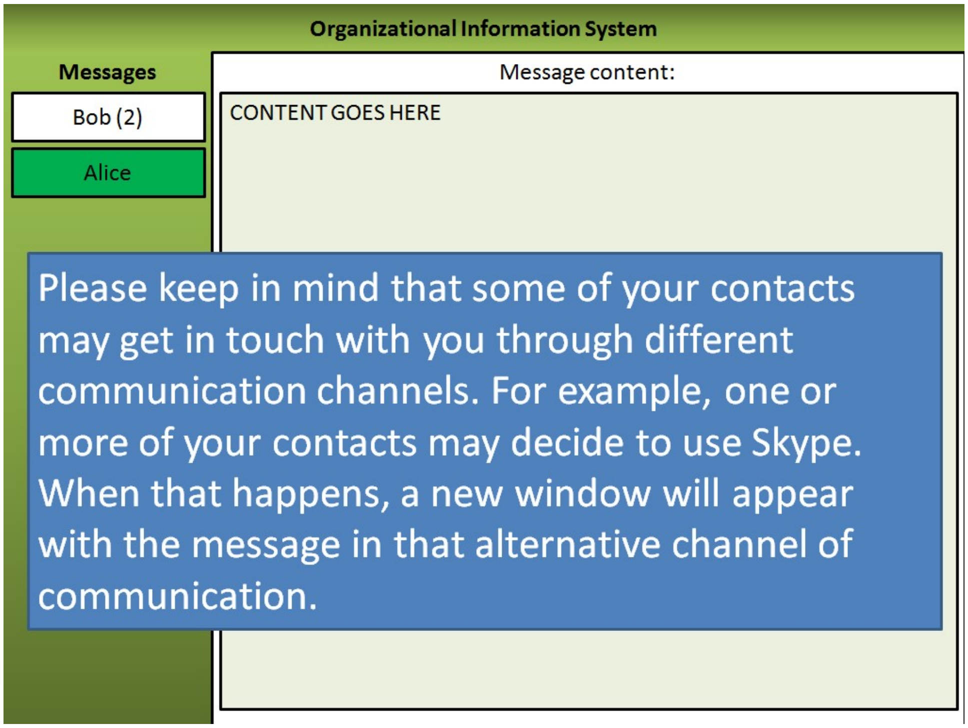


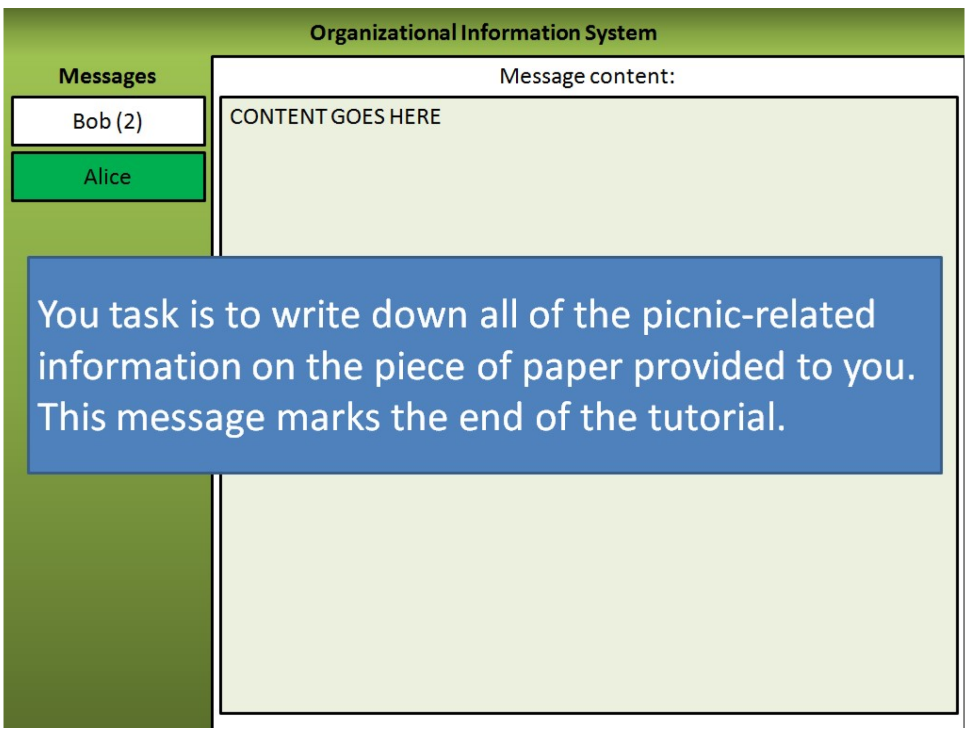

Organizational Information System
Messages
Message content:
CONTENT GOES HERE
The content of the newest message will be shown to you in the "Message Content Window."

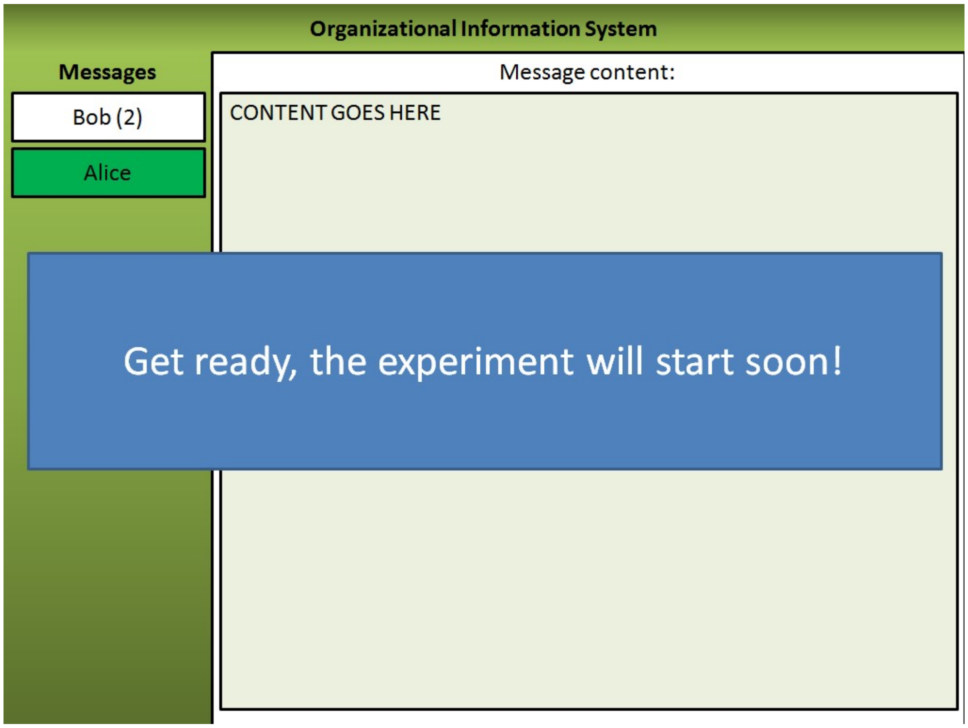

Organizational Information System
Messages
Message content:
Alice
Names of the contact persons who sent you the message will appear on the left side of the screen, under the "Messages" textbox. You have just received a message from Alice.

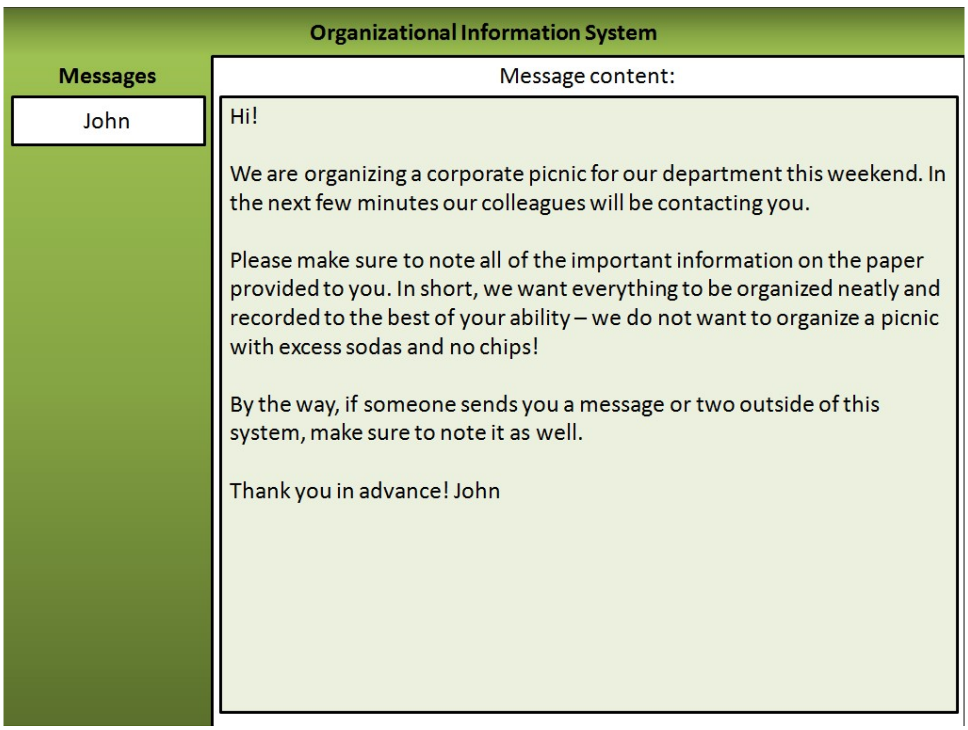

Organizational Information System
Messages
Bob
Alice
Message content:
CONTENT GOES HERE
When you receive a new message, the old message will move one row down and turn green. The newest message will always be highlighted in white. Look, you have received a new message from Bob.

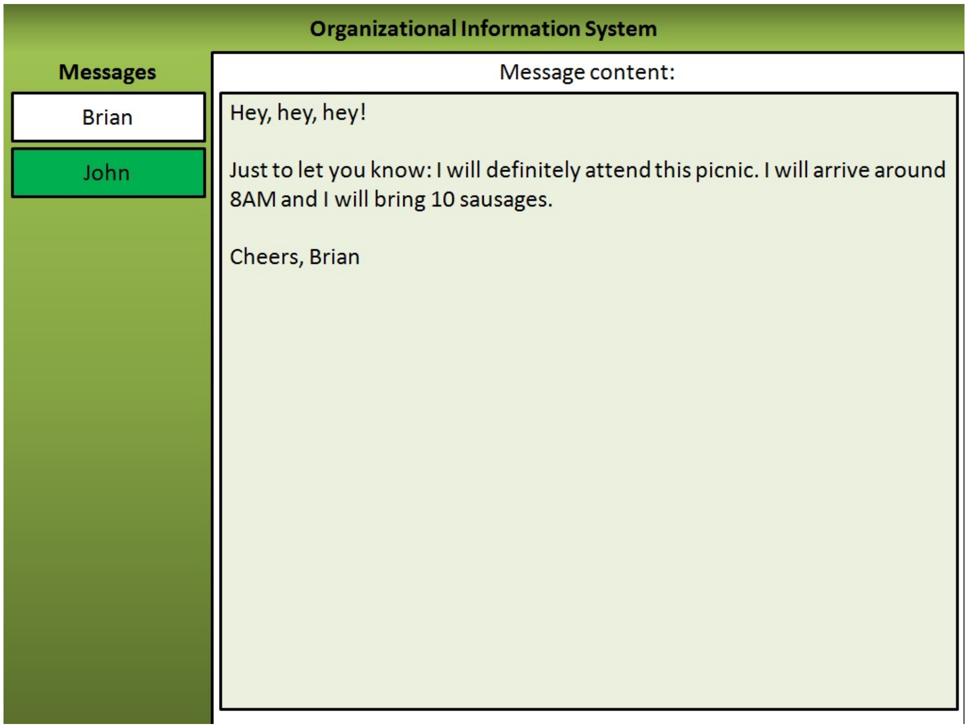

Organizational Information System
Bob (2)
Alice
Message content:
CONTENT GOES HERE
If one contact sends you multiple messages, a message number will appear next to the contact's name. In this specific case, Bob sent you another (second) message. Note the first message not while the newer message is labeled with a number (2).

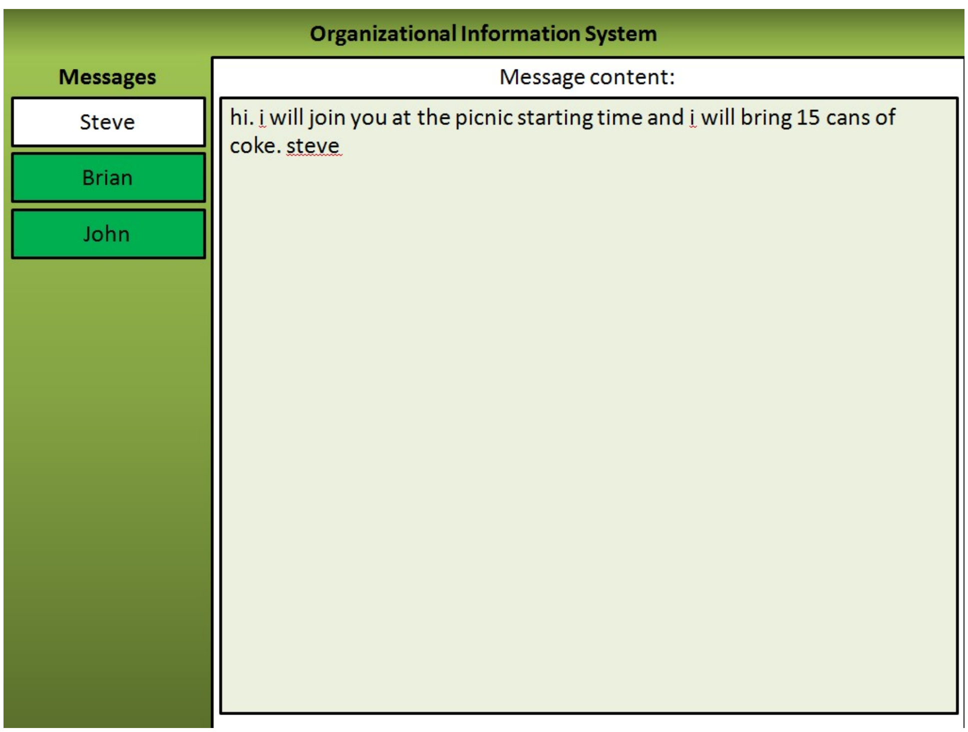

Organizational Information System
Messages
Bob (2)
Alice
Message content:
CONTENT GOES HERE
Please keep in mind that some of your contacts may get in touch with you through different communication channels. For example, one or more of your contacts may decide to use Skype. When that happens, a new window will appear with the message in that alternative channel of communication.

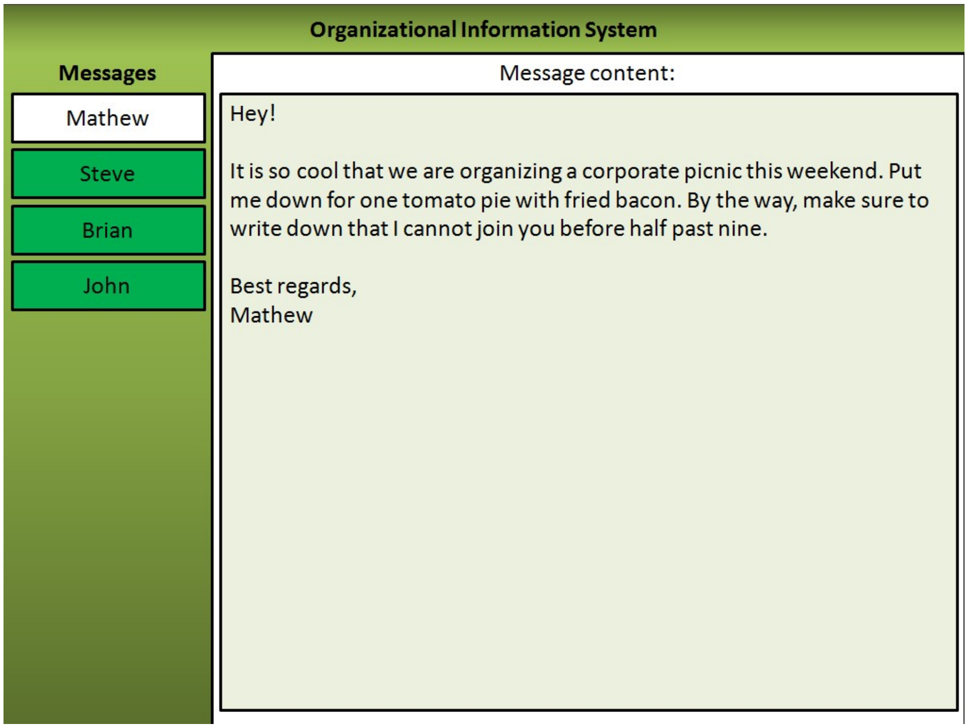

Organizational Information System
Messages
Bob (2)
Alice
Message content:
CONTENT GOES HERE
You task is to write down all of the picnic-related information on the piece of paper provided to you. This message marks the end of the tutorial.

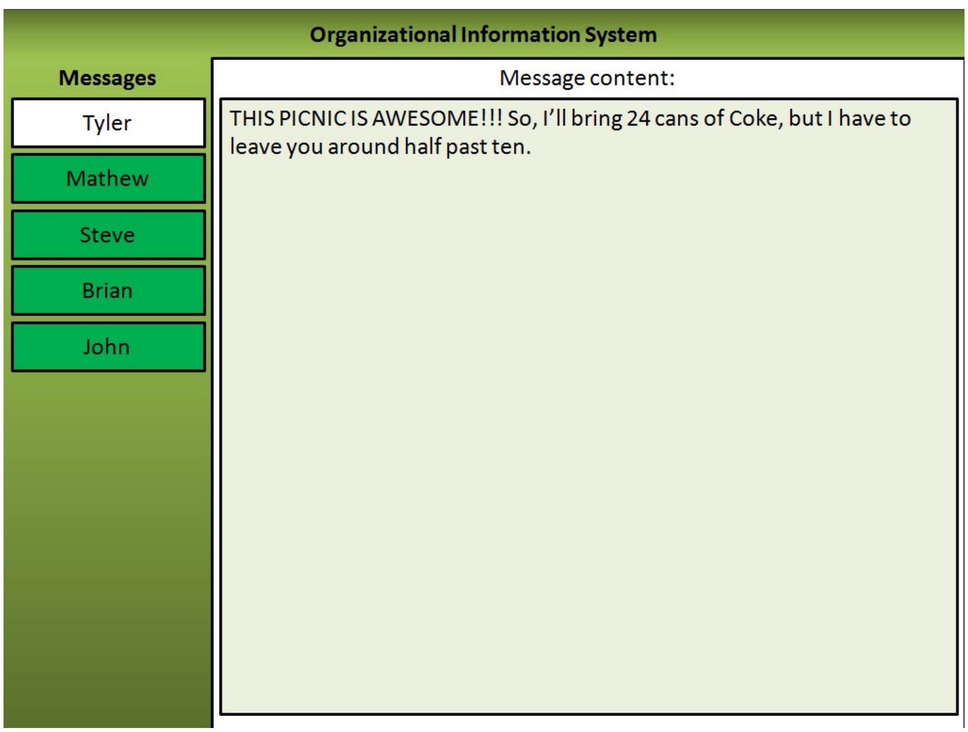

Organizational Information System
Messages
Bob (2)
Alice
Message content:
CONTENT GOES HERE
Get ready, the experiment will start soon!

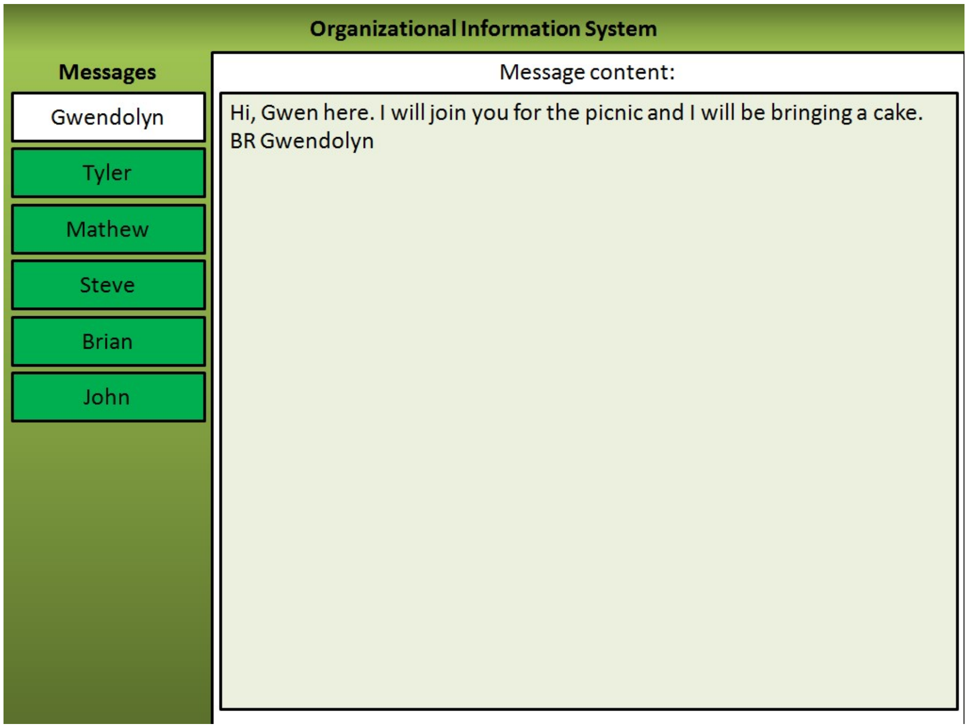

Organizational Information System
Messages
John
Message content:
Hi!
We are organizing a corporate picnic for our department this weekend. In the next few minutes our colleagues will be contacting you.
Please make sure to note all of the important information on the paper provided to you. In short, we want everything to be organized neatly and recorded to the best of your ability – we do not want to organize a picnic with excess sodas and no chips!
By the way, if someone sends you a message or two outside of this system, make sure to note it as well.
Thank you in advance! John

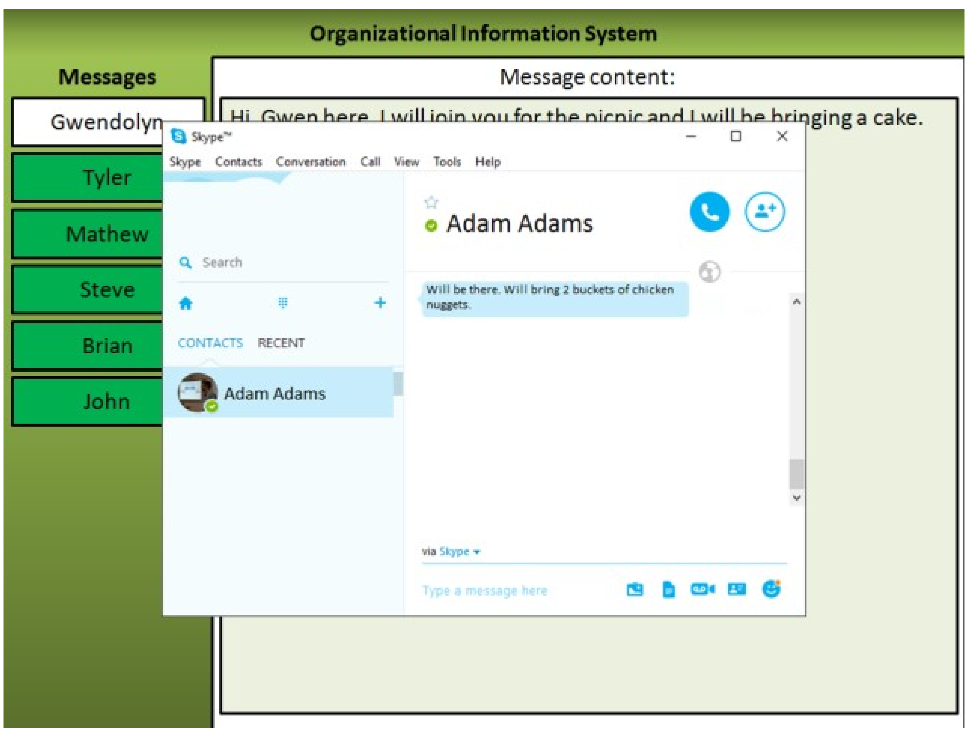

Organizational Information System
Messages
Brian
John
Message content:
Hey, hey, hey!
Just to let you know: I will definitely attend this picnic. I will arrive around 8AM and I will bring 10 sausages.
Cheers, Brian

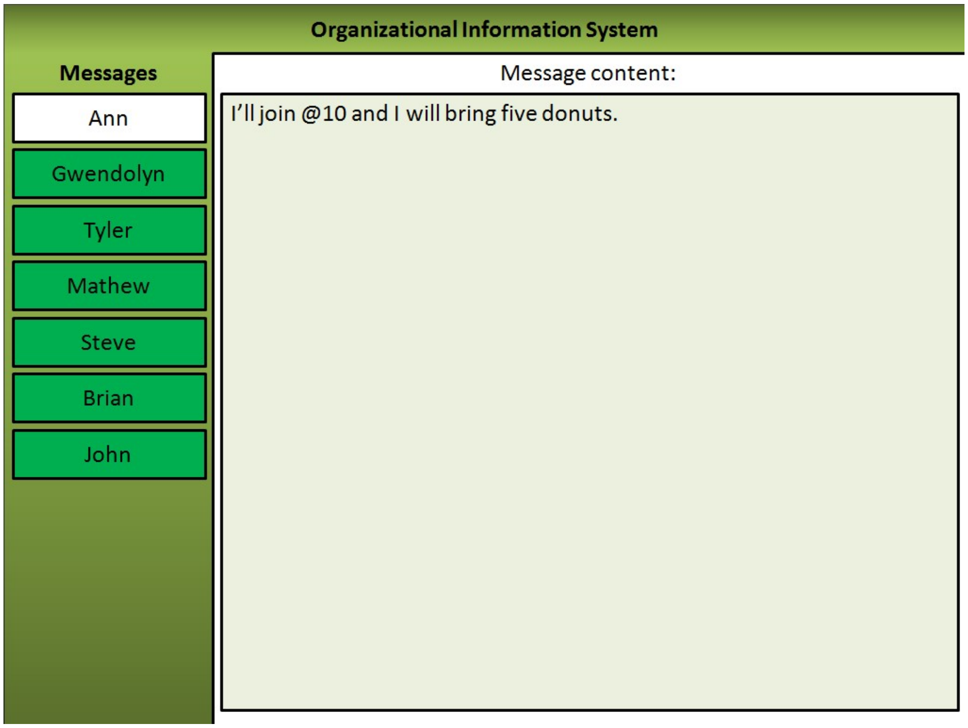

Organizational Information System
Messages
Steve
Brian
John
Message content:
hi. i will join you at the picnic starting time and i will bring 15 cans of coke. steve

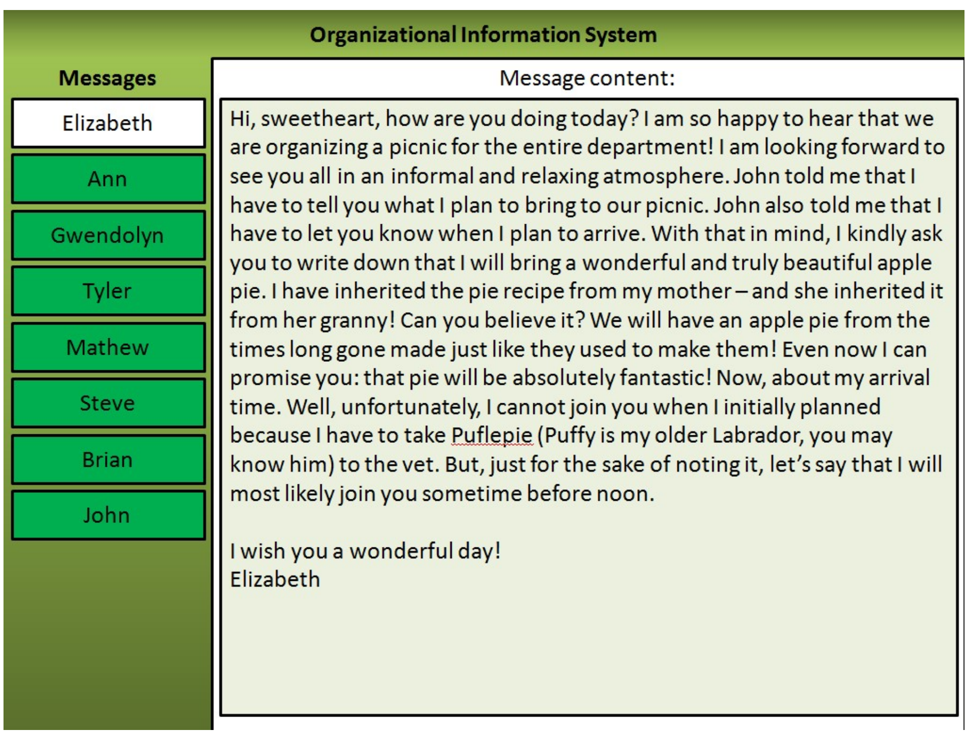

Organizational Information System
Messages
Mathew
Steve
Brian
John
Message content:
Hey!
It is so cool that we are organizing a corporate picnic this weekend. Put me down for one tomato pie with fried bacon. By the way, make sure to write down that I cannot join you before half past nine.
Best regards,
Mathew

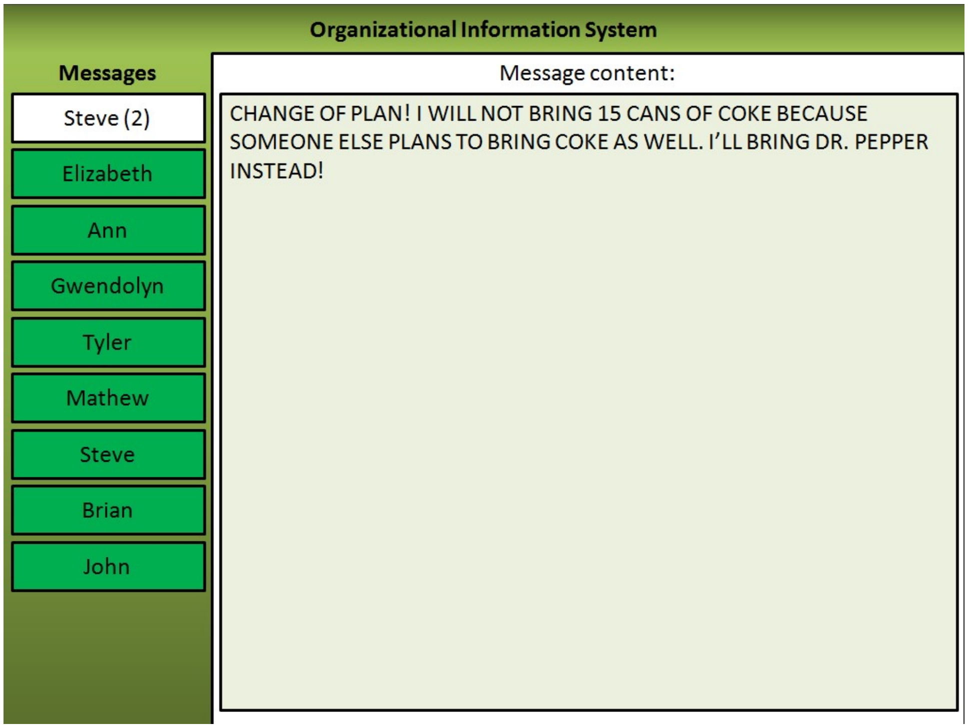

Organizational Information System
Messages
Tyler
Mathew
Steve
Brian
John
Message content:
THIS PICNIC IS AWESOME!!! So, I'll bring 24 cans of Coke, but I have to leave you around half past ten.

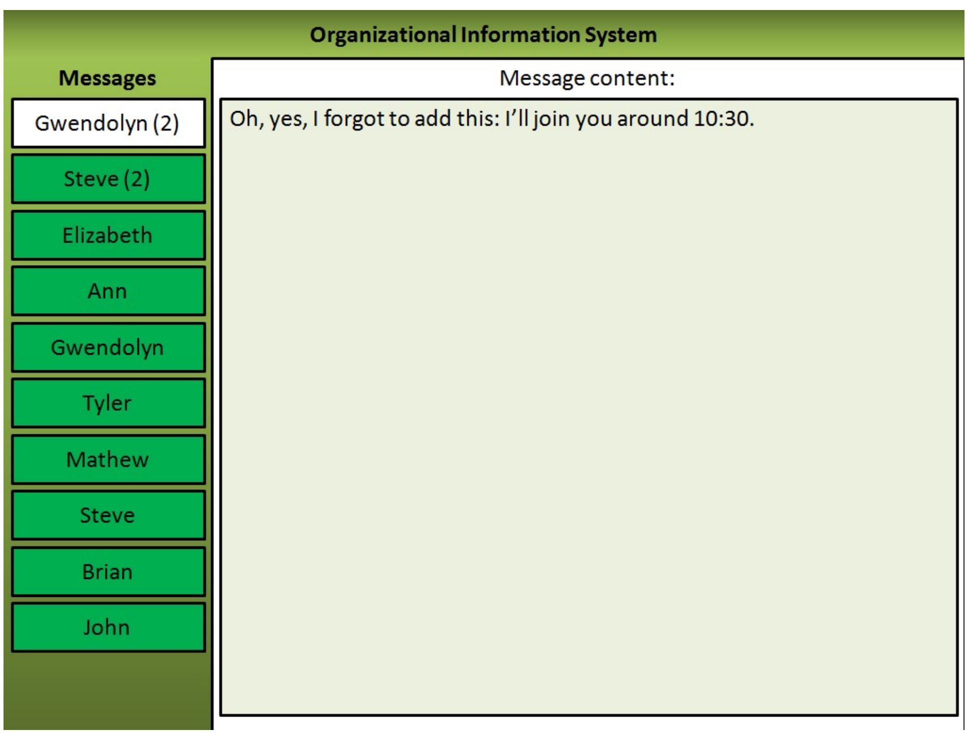

Organizational Information System
Messages
Message content:
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Hi, Gwen here. I will join you for the picnic and I will be bringing a cake.
BR Gwendolyn

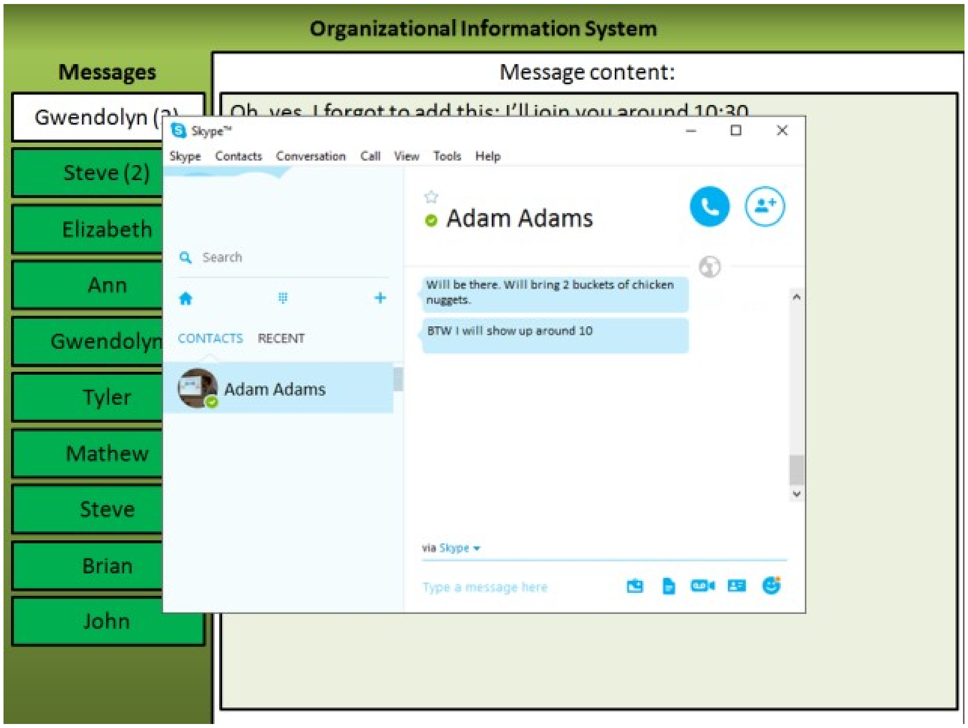

Organizational Information System
Messages
Message content:
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Skype
Skype Contacts Conversation Call View Tools Help
Adam Adams
Search
CONTACTS RECENT
Adam Adams
Will be there. Will bring 2 buckets of chicken nuggets.
via Skype
Type a message here

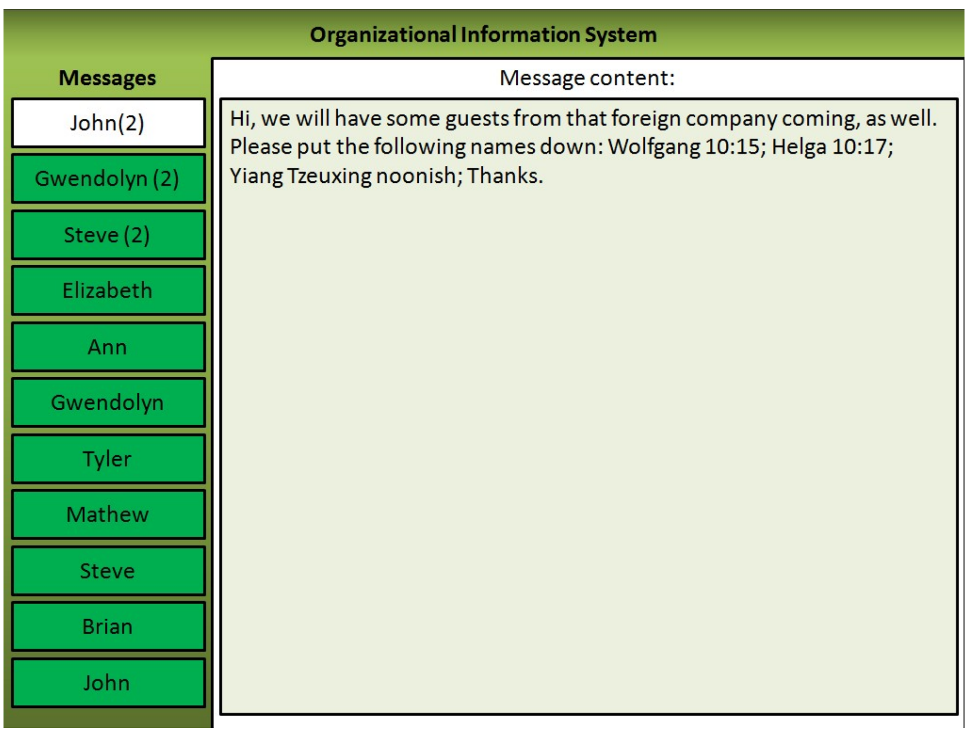

Organizational Information System
Messages
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Message content:
I'll join @10 and I will bring five donuts.

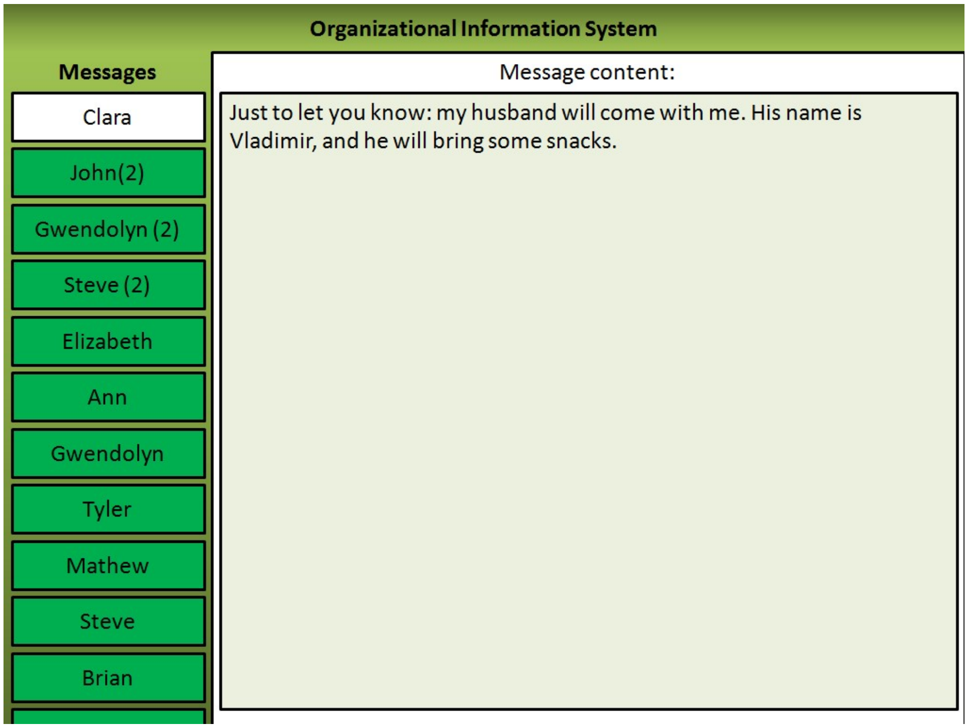

Organizational Information System
Messages
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Message content:
Hi, sweetheart, how are you doing today? I am so happy to hear that we are organizing a picnic for the entire department! I am looking forward to see you all in an informal and relaxing atmosphere. John told me that I have to tell you what I plan to bring to our picnic. John also told me that I have to let you know when I plan to arrive. With that in mind, I kindly ask you to write down that I will bring a wonderful and truly beautiful apple pie. I have inherited the pie recipe from my mother – and she inherited it from her granny! Can you believe it? We will have an apple pie from the times long gone made just like they used to make them! Even now I can promise you: that pie will be absolutely fantastic! Now, about my arrival time. Well, unfortunately, I cannot join you when I initially planned because I have to take Puflepie (Puffy is my older Labrador, you may know him) to the vet. But, just for the sake of noting it, let's say that I will most likely join you sometime before noon.
I wish you a wonderful day!
Elizabeth

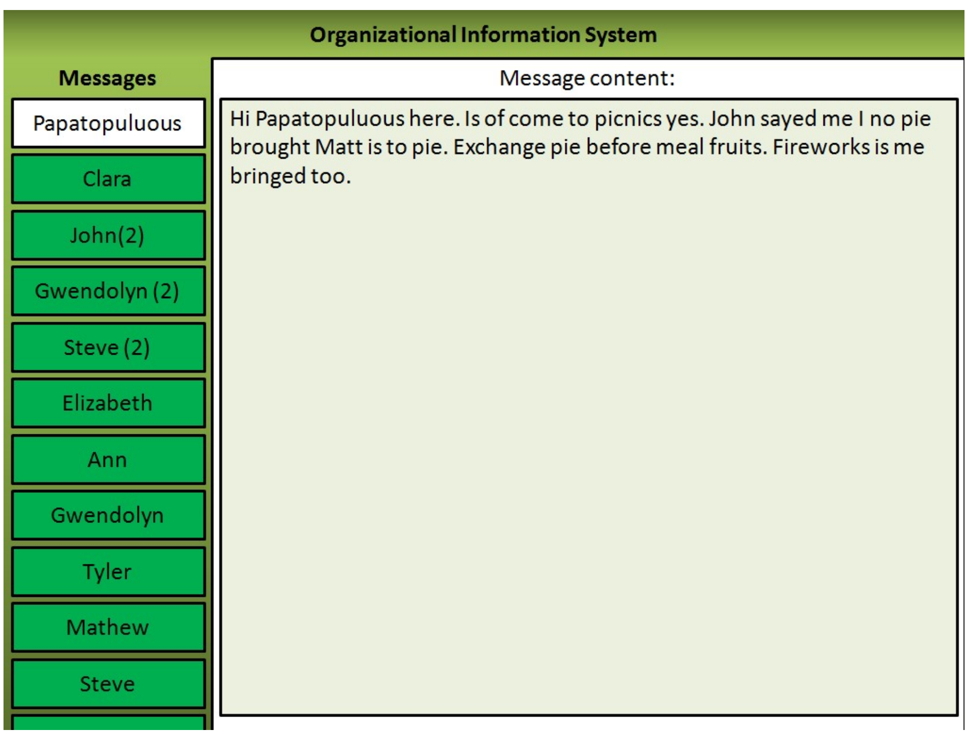

Organizational Information System
Messages
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Message content:
CHANGE OF PLAN! I WILL NOT BRING 15 CANS OF COKE BECAUSE SOMEONE ELSE PLANS TO BRING COKE AS WELL. I'LL BRING DR. PEPPER INSTEAD!

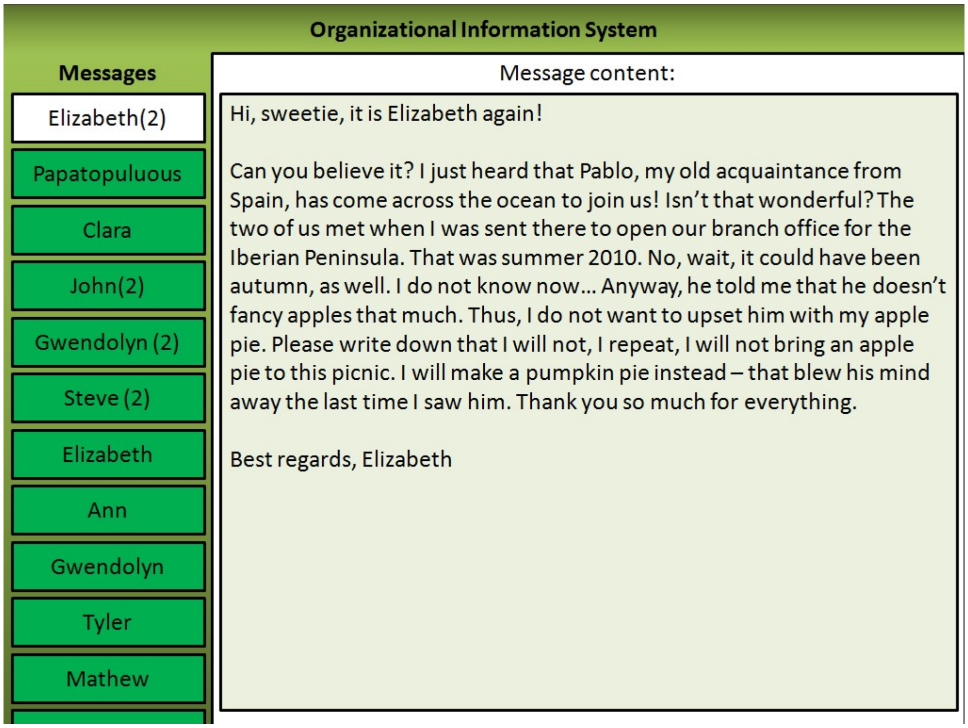

Organizational Information System
Messages
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Message content:
Oh, yes, I forgot to add this: I'll join you around 10:30.

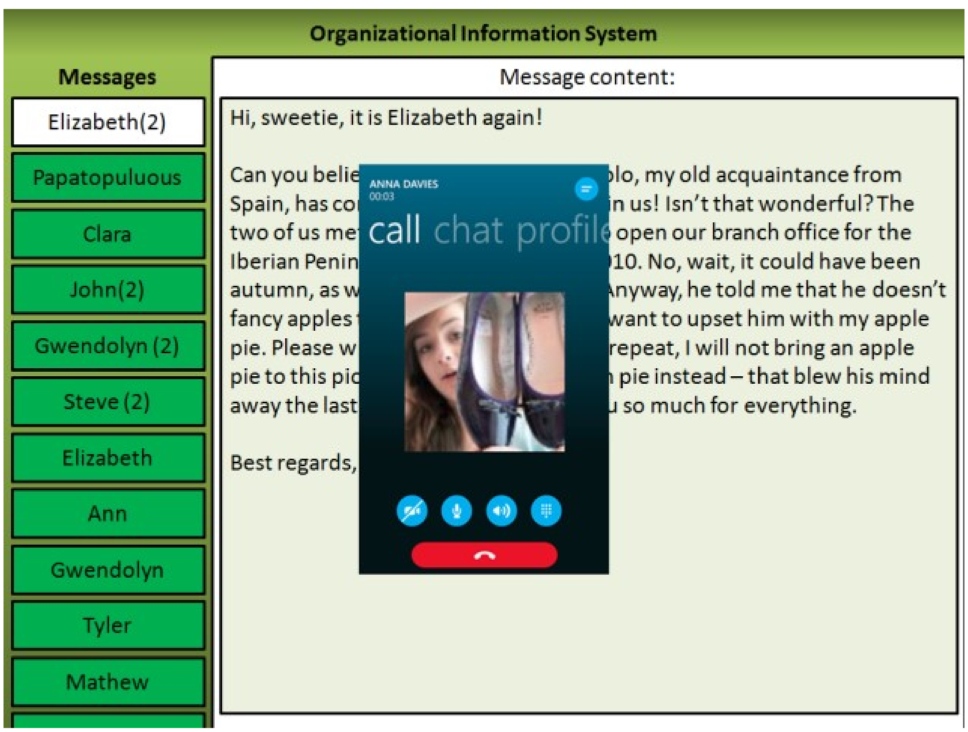

Organizational Information System
Messages
Message content:
Gwendolyn
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Oh, yes, I forgot to add this: I'll join you around 10:30
Skype™
Skype Contacts Conversation Call View Tools Help
Search
CONTACTS RECENT
Adam Adams
Adam Adams
Will be there. Will bring 2 buckets of chicken nuggets.
BTW I will show up around 10
via Skype
Type a message here

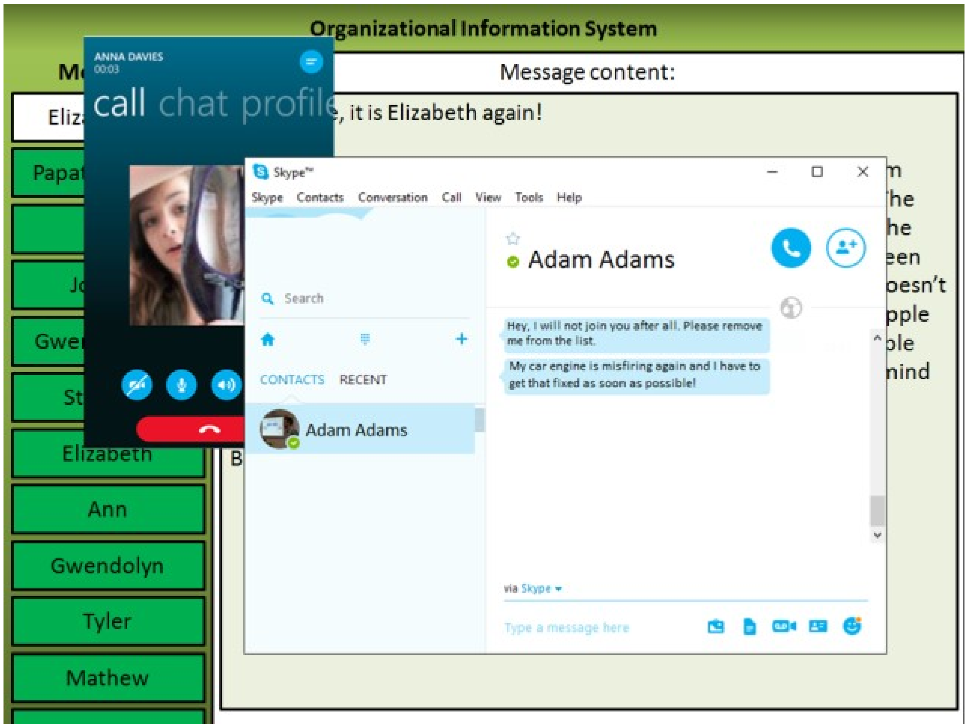

Organizational Information System
Messages
Message content:
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
John
Hi, we will have some guests from that foreign company coming, as well. Please put the following names down: Wolfgang 10:15; Helga 10:17; Yiang Tzeuxing noonish; Thanks.

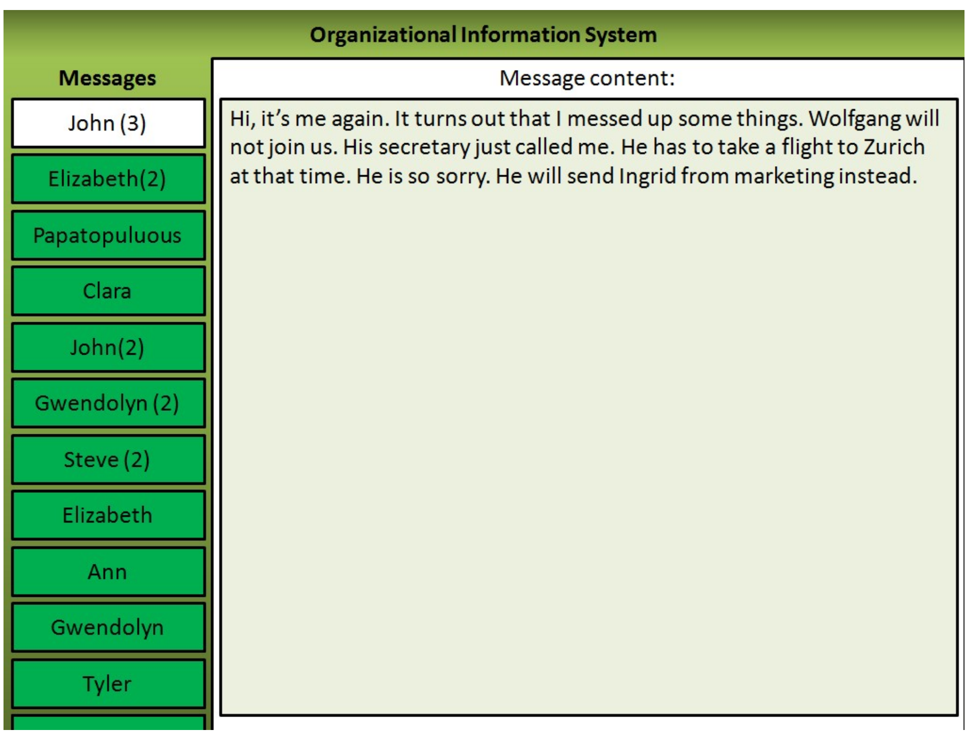

Organizational Information System
Messages
Message content:
Clara
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Brian
Just to let you know: my husband will come with me. His name is Vladimir, and he will bring some snacks.

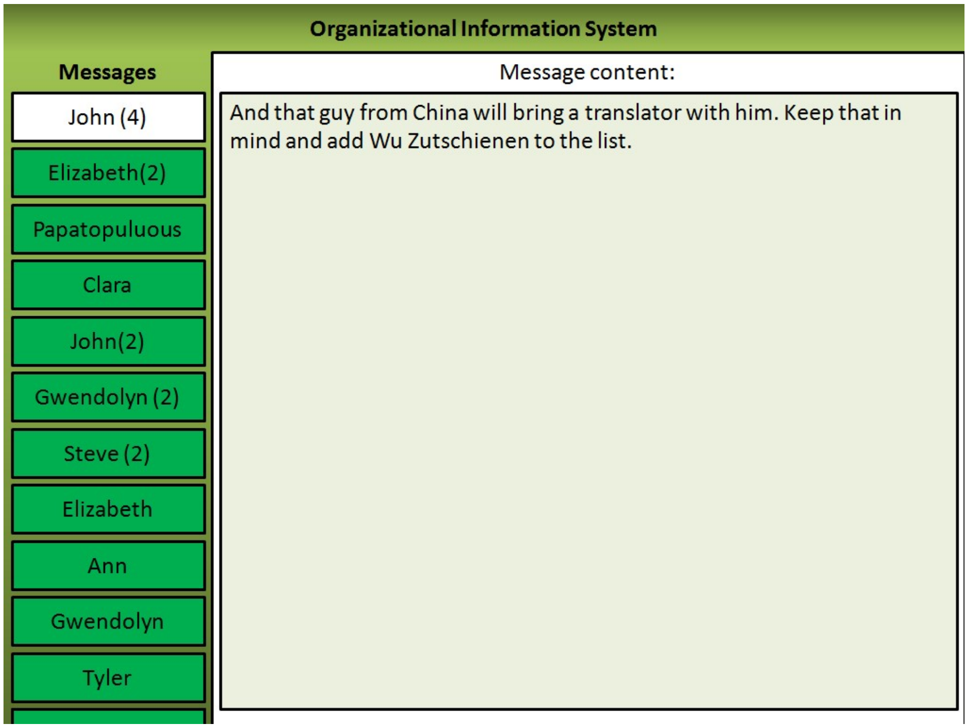

Organizational Information System
Messages
Message content:
Papatopuluous
Clara
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Steve
Hi Papatopuluous here. Is of come to picnics yes. John sayed me I no pie brought Matt is to pie. Exchange pie before meal fruits. Fireworks is me bringed too.


Organizational Information System
Messages
Elizabeth(2)
Papatopuluous
Clara
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Message content:
Hi, sweetie, it is Elizabeth again!
Can you believe it? I just heard that Pablo, my old acquaintance from Spain, has come across the ocean to join us! Isn't that wonderful? The two of us met when I was sent there to open our branch office for the Iberian Peninsula. That was summer 2010. No, wait, it could have been autumn, as well. I do not know now… Anyway, he told me that he doesn't fancy apples that much. Thus, I do not want to upset him with my apple pie. Please write down that I will not, I repeat, I will not bring an apple pie to this picnic. I will make a pumpkin pie instead – that blew his mind away the last time I saw him. Thank you so much for everything.
Best regards, Elizabeth


Organizational Information System
Messages
Elizabeth(2)
Papatopuluous
Clara
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Mathew
Message content:
Hi, sweetie, it is Elizabeth again!
ANNA DAVIES
00:03
call chat profile
Best regards,


Organizational Information System
Message content:
, it is Elizabeth again!
ANNA DAVIES
00:03
call chat profile
Skype™
Skype Contacts Conversation Call View Tools Help
Adam Adams
Search
CONTACTS RECENT
Adam Adams
Hey, I will not join you after all. Please remove me from the list.
My car engine is misfiring again and I have to get that fixed as soon as possible!
via Skype
Type a message here
Elizabeth
Ann
Gwendolyn
Tyler
Mathew


Organizational Information System
Messages
Message content:
John (3)
Elizabeth(2)
Papatopuluous
Clara
John(2)
Gwendolyn (2)
Steve (2)
Elizabeth
Ann
Gwendolyn
Tyler
Hi, it's me again. It turns out that I messed up some things. Wolfgang will not join us. His secretary just called me. He has to take a flight to Zurich at that time. He is so sorry. He will send Ingrid from marketing instead.



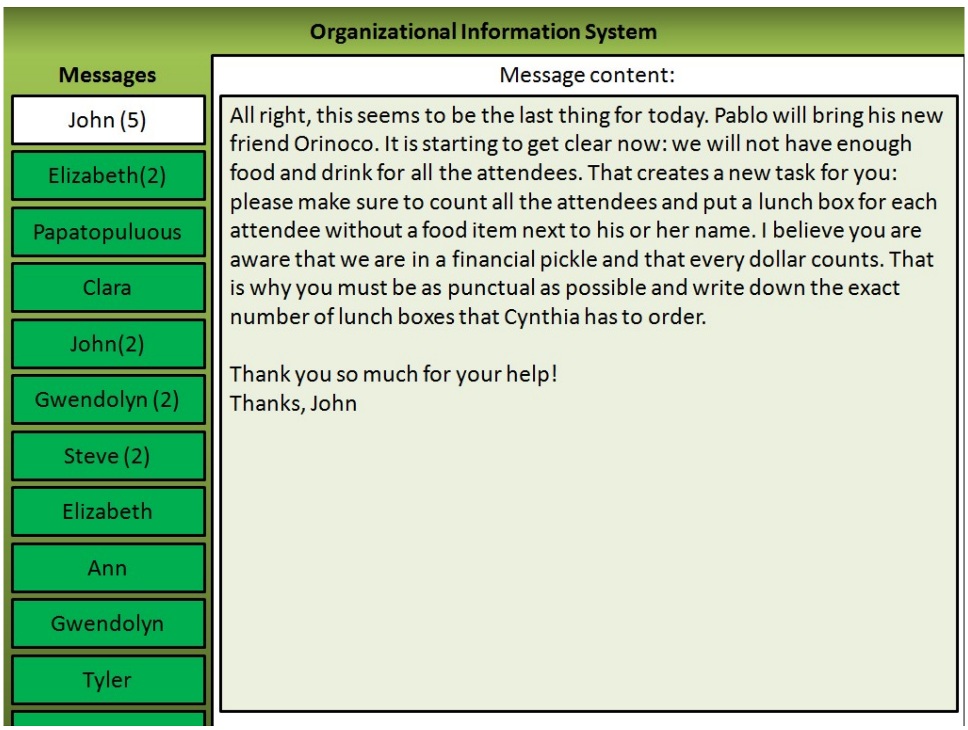


Figure C.1: Experimental Software Interface

APPENDIX D

Experimental Software Content

This appendix provides content which would have appeared on the specific experimental setting described in Appendix C. Msq# rubric contains number for the specific message. T# symbol represent tutorial messages. M# symbol represent actual messages participants were instructed to record. Message numbers do not represent the actual order of appearance of messages throughout the experiment. Message numbers represent the way in which messages were ordered for the purposes of data analysis. MsgContent Rubric is populated with the verbatim content that was displayed to the participants. MsgType rubric marks the type of the message. TXT stands for textual message within the experimental system. SM is used for textual messages displayed in Skype. SV is reserved for voice messages displayed in Skype. WTXT marks textually dense messages. Table D.1. lists all messages in chronological order compatible with Chapter Four of this dissertation. However, as a result of experimental randomization processes, some participants received these messages in a different chronological order.

Table D.1: Message Content

Msg#	MsgContent	MsgType
T1	Welcome! This application shows you the messages you will receive from your contacts throughout this experiment.	TXT
T2	The content of the newest message will be shown to you in the “Message Content Window.”	TXT

Table D.1: Message Content--Continued

Msg#	MsgContent	MsgType
T3	Names of the contact persons who sent you the message will appear on the left side of the screen, under the “Messages” textbox. You have just received a message from Alice.	TXT
T4	When you receive a new message, the old message will move one row down and turn green. The newest message will always be highlighted in white. Look, you have received a new message from Bob.	TXT
T5	If one contact sends you multiple messages, a message number will appear next to the contact’s name. In this specific case, Bob sent you another (second) message. Note the first message is labeled with a #1 and the newer message with a #2.	TXT
T6	Please keep in mind that some of your contacts may get in touch with you through different communication channels. For example, one or more of your contacts may decide to use Skype. When that happens, a new window will appear with the message in that alternative channel of communication.	TXT
T7	You task is to write down all of the picnic-related information on the piece of paper provided to you. This message marks the end of the tutorial.	TXT
T8	Get ready, the experiment will start soon!	TXT
M1	Hi! We are organizing a corporate picnic for our department this weekend. In the next few minutes our colleagues will be contacting you. Please make sure to note all of the important information on the paper provided to you. In short, we want everything to be organized neatly and recorded to the best of your ability – we do not want to organize a picnic with excess sodas and no chips! By the way, if someone sends you a message or two outside of this system, make sure to note it as well. Thank you in advance! NAME	TXT
M2	Hey, hey, hey! Just to let you know: I will definitely attend this picnic. I will arrive around 8AM and I will bring 10 sausages. Cheers, NAME	TXT
M3	Hi. I will join you at the picnic starting time and I will bring 15 cans of Coke. NAME	TXT

Table D.1: Message Content--Continued

Msg#	MsgContent	MsgType
M4	Hey! It is so cool that we are organizing a corporate picnic this weekend. Put me down for one tomato pie with fried bacon. By the way, make sure to write down that I cannot join you before half past nine. Best regards, NAME	TXT
M5	THIS PICNIC IS AWESOME!!! So, I'll bring 24 cans of Coke, but I have to leave you around half past ten.	TXT
M6	Hi, NAME here. I will join you for the picnic and I will be bringing a cake. BR NAME	TXT
M7	Will be there. Will bring 2 buckets of chicken nuggets.	SM
M8	I'll join @10 and I will bring five donuts.	TXT
M9	Hi, sweetheart, how are you doing today? I am so happy to hear that we are organizing a picnic for the entire department! I am looking forward to see you all in an informal and relaxing atmosphere. NAME told me that I have to tell you what I plan to bring to our picnic. NAME also told me that I have to let you know when I plan to arrive. With that in mind, I kindly ask you to write down that I will bring a wonderful and truly beautiful apple pie. I have inherited the pie recipe from my mother – and she inherited it from her granny! Can you believe it? We will have an apple pie from the times long gone made just like they used to make them! Even now I can promise you: that pie will be absolutely fantastic! Now, about my arrival time. Well, unfortunately, I cannot join you when I initially planned because I have to take Puflepie (Puffy is my older Labrador, you may know him) to the vet. But, just for the sake of noting it, let's say that I will most likely join you sometime before noon. I wish you a wonderful day! NAME	WTXT
M10	CHANGE OF PLAN! I WILL NOT BRING 15 CANS OF COKE BECAUSE SOMEONE ELSE PLANS TO BRING COKE AS WELL. I'LL BRING DR. PEPPER INSTEAD!	TXT
M11	Oh, yes, I forgot to add this: I'll join you around 10:30.	TXT
M12	BTW I will show up around 10	SM
M13	Hi, we will have some guests from that foreign company coming, as well. Please put the following names down: NAME TIME; NAME TIME; NAME TIME; Thanks.	TXT

Table D.1: Message Content--Continued

Msg#	MsgContent	MsgType
M14	Just to let you know: my husband will come with me. His name is NAME, and he will bring some snacks.	TXT
M15	Hi NAME here. Is of come to picnics yes. NAME sayed me I no pie brought NAME is to pie. Exchange pie before meal fruits. Fireworks is me bringed too.	TXT
M16	Hi, sweetie, it is NAME again! Can you believe it? I just heard that NAME, my old acquaintance from Spain, has come across the ocean to join us! Isn't that wonderful? The two of us met when I was sent there to open our branch office for the Iberian Peninsula. That was summer 2010. No, wait, it could have been autumn, as well. I do not know now… Anyway, he told me that he doesn't fancy apples that much. Thus, I do not want to upset him with my apple pie. Please write down that I will not, I repeat, I will not bring an apple pie to this picnic. I will make a pumpkin pie instead – that blew his mind away the last time I saw him. Thank you so much for everything. Best regards, NAME	WTXT
M17	Hi, I am calling from my wife's account. My name is NAME and I will bring non-alcoholic champagne to our picnic. Thanks.	SV
M18	Hey, I will not join you after all. Please remove me from the list. My car engine is misfiring again and I have to get that fixed as soon as possible!	SM
M19	Hi, it's me again. It turns out that I messed up some things. NAME will not join us. His secretary just called me. He has to take a flight to Zurich at that time. He is so sorry. He will send NAME from marketing instead.	TXT
M20	And that guy from China will bring a translator with him. Keep that in mind and add NAME to the list.	TXT

Table D.1: Message Content--Continued

Msg#	MsgContent	MsgType
M21	All right, this seems to be the last thing for today. NAME will bring his new friend NAME. It is starting to get clear now: we will not have enough food and drink for all the attendees. That creates a new task for you: please make sure to count all the attendees and put a lunch box for each attendee without a food item next to his or her name. I believe you are aware that we are in a financial pickle and that every dollar counts. That is why you must be as punctual as possible and write down the exact number of lunch boxes that NAME has to order. Thank you so much for your help! Thanks, NAME	WTXT

For the purposes of this research the experimental software graphical user interfaces was used with two language variants: English and Serbo-Croatian.

APPENDIX E

Experimental Software Pre-Testing

The combination of experimental software and the CND used in this research was pre-tested prior to conducting this experiment. The results of the preliminary study were presented at Gmunden 2016 NeuroIS retreat (Milic 2017). The part of the manuscript in which the device is tested is presented and expanded here for the purposes of this dissertation.

The selected device, Neurosky Mindwave headband (headband in the following text), was used to gather data from a group of 12 test subjects. Neuro Experimenter software v3.28 was used to access the API of the headband and to record EEG based BCI data ("NeuroExperimenter" n.d.). All participating subjects of this pilot study were healthy PhD students at a medium-sized private university in the southern part of the United States. All subjects were right handed, and between the age of 27 and 35. Two participants were female. All recordings were gathered in a standard office environment while subjects were working on light office tasks that required them to use a computer (e.g. checking email inbox, browsing the Internet and arranging files etc.). Participants were explicitly told to remove the headband as soon as they were done with their office tasks. According to the manufacturer's specification, Headband is able to detect Alpha 1, Alpha 2, Beta 1, Beta 2, Gamma 1, Gamma 2, Delta and Theta[1] waves.

[1] For additional information about EEG Frequency Bands please consult Müller-Putz et al. 2015/ p.918

According to manufacturer's specification, the headband used in this pilot study records brainwave readings every 500ms, via a "cluster sensor" positioned on the participant's forehead and targeted at the prefrontal cortex (PFC). PFC is known to be the executive center of the human brain (Dimoka et al. 2012; Dimoka, Pavlou, et al. 2010), where decision actions (e.g. calculations) are performed. Descriptive statistics of the gathered data are presented in Table E.1.

Table E.1: Descriptive Statistics Test Data

EEG Bands	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Delta	16217	.50	98.64	47.48	27.12	735.28
Theta	16217	.17	81.30	21.22	13.01	169.25
Alpha1	16217	.01	71.88	7.45	6.93	47.98
Alpha2	16217	.04	58.22	6.60	6.12	37.45
Beta1	16217	.06	45.21	6.08	5.57	31.02
Beta2	16217	.04	46.94	5.58	5.09	25.89
Gamma1	16217	.02	37.46	3.26	3.25	10.54
Gamma2	16217	.01	30.44	2.33	2.41	5.83

In summation, this pilot study demonstrated that a CND can be used to collect EEG signals. Furthermore, CND clearly and unambiguously reacted to the external stimuli in the way that literature (CITE) suggested it should. Naturally, spatial and temporal resolutions of the recordings are not identical to the standards that are generally employed in EEG studies (Müller-Putz et al. 2015b) – instead of dozens of simple sensors, the headband used in this pilot study has only one "clustered sensor"; and instead of the recommended 200ms temporal resolution, this device is capable of recording only 500 ms intervals. However, according to criteria presented in Kübler et al. 2001 (Kübler et al. 2001), the headband used in this study fits all the requirements for a neuro sensor because it successfully detected the electrophysiological activity of the user's brain, recorded the signals at 97.62% accuracy (which is above the proposed 70% threshold) and bypassed most of the stated limitations. This pilot study paves the way for using CNDs to better understand and detect one of the growing technostress phenomena known as Information Overload (IO).

APPENDIX F

Internal Review Board Approval

This dissertation was approved by the Internal Review Board (IRB) of Baylor University. The initial IRB application was submitted on Feb 02 2016, conditionally accepted on April 4 2016 and fully approved after a series of changes on March 28 2017. The IRB submission case Baylor IRBnet ID is 871609-4. The approval letter is presented below. I am eternally grateful to all involved IRB personnel. The diligent guidance and exemplary expedience they have demonstrated throughout this process serve as an example to the entire academia and all Internal Review Boards across the Universes.

BAYLOR
UNIVERSITY

INSTITUTIONAL REVIEW BOARD – PROTECTION OF HUMAN SUBJECTS IN RESEARCH

NOTICE OF EXPEDITED APPROVAL – INITIAL REVIEW

Principal Investigator:	Nash Milic
Study Title:	Communication channel effects on elementary cognitive performances
IRB Reference #:	871609
Date of Conditional Approval:	04/04/2016
Date Response Accepted:	03/27/2017
Date of Expiration:	04/04/2017
Expedited Category:	4 & 7

The above referenced human subjects research project has been approved by the Baylor University Institutional Review Board (IRB). Specifically, the IRB reviewed and approved the following documents:

- IRB Application, submitted on 03/23/2017
- Response to Required Modifications Form, submitted on 03/14/2017
- Protocol, submitted 03/23/2017
- Consent Form, submitted on 03/20/2017
- Interview questions, submitted on 02/16/2016

This approval is limited to the activities described in the approved protocol and application. In accordance with this approval, general conditions for the conduct of research are attached.

Per your submission, your approved enrollment is: **60**.

Any change to the approved research (including changes to targeted enrollment), must receive prior IRB approval.

For questions concerning this approval, contact Deb Penney at 254-710-3708 or Debbie_Penney@Baylor.edu

Sincerely,

David W. Schlueter

David W. Schlueter, Ph.D.
Chair, Baylor IRB

OFFICE OF THE VICE PROVOST FOR RESEARCH

One Bear Place #97310 • Waco, TX 76798-7310 • (254) 710-3708 • FAX (254) 710-7309 • http://www.baylor.edu/research/irb/

General Conditions of Approval and Investigator Responsibilities

- The principal investigator (PI) is responsible for personally conducting or supervising the conduct of the research and for protecting the rights, safety, and welfare of the enrolled subjects. All human-subjects research must be conducted in an ethical manner and in accordance with all federal, state, and local laws and regulations, institutional policies, and requirements or determinations of the IRB.
- The PI should have a plan for supervision and oversight of the research. The PI may delegate study-related tasks to research personnel qualified by training and experience to perform the delegated tasks, but must adequately supervise personnel to whom tasks are delegated.
- The PI or another specific qualified individual must be available to subjects to answer questions or provide care during the research.
- The research should not be initiated without adequate resources and should be stopped if the necessary resources become unavailable. These resources might include research personnel, space, equipment, time, and availability of medical or psychological care for problems that arise during participation in the research.
- The PI must ensure that:
  - IRB approval is obtained prior to initiation of the research;
  - The research is conducted in accordance with the IRB-approved protocol, including, when applicable, the approved recruitment and consent procedures;
  - When informed consent is required, informed consent is obtained prior to the initiation of any study-related procedures and documented using the current IRB-approved research consent form;
  - When FDA-regulated products are being investigated or used, they are managed and controlled as required by institutional policy and FDA regulations;
  - Changes to the IRB-approved protocol and/or the research consent form are not initiated without IRB approval unless necessary to eliminate apparent immediate hazards to the subject;
  - Unanticipated problems involving risks to subjects or others (including adverse events) are reported promptly to the IRB;
  - When applicable, Data and Safety Monitoring Board/Data Monitoring Committee or other monitoring group reports are submitted promptly to the IRB for review;
  - Continuing review is conducted prior to expiration of IRB approval;
  - Should IRB approval lapse, research procedures, such as recruitment and enrollment of subjects, study procedures on currently enrolled subjects, review of health/medical records, collection of tissue or other samples, or analysis of data, are not conducted until the IRB re-approves the research or until special permission is obtained from the IRB to continue previously enrolled subjects because it is in their best interests to do so;
  - When the research has been completed or is being closed out prior to completion, a Research Closure Form is submitted to the IRB;
  - Adequate and accurate research records are kept and retained as required by the IRB and, when applicable, by the sponsor or FDA; and
  - Research records are made available to the IRB, the Office of the Vice Provost for Research, the sponsor, and when applicable, the Office for Human Research Protections (OHRP), and the Food and Drug Administration (FDA) upon request for monitoring and oversight of the research.

OFFICE OF THE VICE PROVOST FOR RESEARCH

One Bear Place #97310 • Waco, TX 76798-7310 • (254) 710-3763 • FAX (254) 710-7309

Figure F.1: Baylor IRB Letter of Approval

APPENDIX G

Consent Form

This Baylor University

MIS Department

Consent Form for Research

PROTOCOL TITLE: Communication channel effects on elementary cognitive performances

PRINCIPAL INVESTIGATOR: Nash Milic

Introduction

Please read this form carefully. The purpose of this form is to provide you with important information about taking part in a research study. If any of the statements or words in this form are unclear, please let us know. We would be happy to answer any questions. You have the right to discuss this study with another person who is not part of the research team before making your decision whether or not to be in the study.

This study is designed for subjects over the age of 18. If you are not 18 or older you should not participate.

Taking part in this research study is up to you. If you decide to take part in this research study we will ask you to sign this form. We will give you a copy of the signed form.

The person in charge of this study is Nash Milic (PhD student, under advisement of Prof. Dorothy E. Leidner). We will refer to these persons as the "researcher/s" throughout this form.

Why is this study being done?

The purpose of this study is to further the knowledge on elementary cognitive performances. We are asking you to take part in this study because you are accustomed with digital technologies, and as such very likely to be able to express your video watching experiences.

About 60 subjects will take part in this research study at Baylor University.

How long will I take part in this research study?

We expect that you will be in this research study for **around 30 minutes**. During this time, we will ask you to browse the internet, play non-violent games and create a picnic list while wearing a light headband.

What will happen if I take part in this research study?

If you agree to take part in this study, we will ask you to sign the consent form before we do any study procedures. After that, we will shortly brief you about the purpose of this study. When the briefing is finished, we will ask you to put a headband and oximeter and to browse Internet, play games and create a picnic list. The equipment you would be instructed to wear is a consumer grade neural interface, which is legally available for sale.

To the best of our knowledge, taking part in this study **will not hurt you**. To the best of our knowledge, our equipment will not cause any harm to you.

Loss of Confidentiality

A risk of taking part in this study is the possibility of a loss of confidentiality. Loss of confidentiality includes having your personal information shared with someone who is not on the study team and was not supposed to see or know about your information. The researcher plans to protect your confidentiality. Their plans for keeping your information private are described later in this consent form.

There are no benefits to you from taking part in this research.

You may choose not to take part in this research study.

Storing Study Information for Future Use

We would like to store your study information for a 3 years period. We might use it for future research related elementary cognitive performances. We will label all your study information with a code instead of your name. The key to the code connects your name to your study information. The researcher will keep the code in a biometrically secured and password protected computer.

Future use of study information is **optional** for this study**.** If you do not want your information to be used for future research, you should not be in this study.

How Will You Keep My Study Records Confidential?

We will keep the records of this study confidential by storing all files on biometrically protected devices**.** We will make every effort to keep your records confidential. However, there are times when federal or state law requires the disclosure of your records.

The following people or groups may review your study records for purposes such as quality control or safety:

The Researchers and any member of their research team

Authorized members of Baylor University who may need to see your information, such as administrative staff members from the Office of the Vice Provost for Research and members of the Institutional Review Board (a committee which is responsible for the ethical oversight of the study)

The sponsor or funding agency for this study

Federal and state agencies that oversee or review research (such as the HHS Office of Human Research Protection or the Food and Drug Administration)

The study data will be stored on a biometrically protected device.

The results of this study may also be used for teaching, publications, or presentations at professional meetings. If your individual results are discussed, your identity will be protected by using a code number or pseudonym rather than your name or other identifying information.

Study Participation and Early Withdrawal

Taking part in this study is your choice. You are free not to take part or to withdraw at any time for any reason. No matter what you decide, there will be no penalty or loss of benefit to which you are entitled. If you decide to withdraw from this study, the information that you have already provided will be kept confidential. You cannot withdraw information collected prior to your withdrawal.

You may choose not to be in the study or to stop being in the study before it is over at any time. This will not affect your class standing or your grades at Baylor University. You will not be offered or receive any special consideration if you take part in this research study.

You may choose not to be in the study or to stop being in the study before it is over at any time. You will not be offered or receive any special consideration if you take part in this research study.

The researcher may take you out of this study without your permission. This may happen because:

The researcher thinks it is in your best interest

You can't make the required study visits

Other administrative reasons

Will I get paid for taking part in this research study?

You will not be paid for taking part in this study.

What will it cost me to take part in this research study?

There are no costs to you for taking part in this research study.

What if I have any questions or concerns about this research study?

You can contact us via email with any concerns or questions about the research. Please direct your emails to:

Nash_Milic@baylor.edu

If you want to speak with someone **not** directly involved in this research study, you may contact the Baylor University IRB through the Office of the Vice Provost for Research at 254-710-1438. You can talk to them about:

Your rights as a research subject

Your concerns about the research

A complaint about the research

Indicate your decision for the below optional research discussed earlier in this form:

Optional Consent for future research with study information:

Do you agree to let us store your study information for future research related to user experience?

______YES ______NO _______INITIALS

Future Contact

We may like to contact you in the future either to follow-up to this study or to see if you are interested in other studies taking place at Baylor University.

Do you agree to let us contact you in the future?

______YES ______NO _______INITIALS

Statement of Consent

I have read the information in this consent form including risks and possible benefits. I have been given the chance to ask questions. My questions have been answered to my satisfaction, and I agree to participate in the study.

_____________________________________ ____________________

Signature of Subject Date

Signature of Person Obtaining Consent:

I have explained the research to the subject and answered all his/her questions. I will give a copy of the signed consent form to the subject.

_______________________________________ ______________________

Signature of Person Obtaining Consent Date

APPENDIX H

Supplemental Data

In addition to the data collected from the CND I have also collected two sources of supplemental data for this dissertation. The first data source comes from the oximeter, while the second data source comes from the documents the participants were asked to fill during the Office task experimental sub-phase.

For the purpose of this dissertation, I use CMS 50D+ Blue Finger Pulse Oximeter. This instrument can record heart rate and blood oxygen saturation (SpO_2). Heart rate is understood as the number of heart beats per minute. I use heart rate to control for potential stressors. The normal heart rate for sedentary activities ranges from 60 to 100 heart beats per minute, with minor alterations based on age and general health condition (AHA 2015; Laskowski 2015). Table H.1 provides descriptive statistics for this data source. In general, all heart rate values were within the normal heart rates. This means that it is highly unlikely that the EEG frequency bands I measured were influenced by the external factors like stress and fear. All SpO_2 readings were above 95%, which also fits well within the recommended guidelines (Mayo Clinic 2015). Textual data was also collected during the Office task sub-phase. As explained in Chapter Three, all participants were provided with a printed sheet of paper. This paper sheet contained a table with four columns named “Name”, “Time”, “Item” and “Note”. Participants were instructed to use these sheets to fill in the names of the attendees, times of arrival, items to be brought and additional notes where applicable. Upon closer examination of the textual data, a set of patterns emerged. These patterns are elaborated in Table H.2.

Table H.1: Heart Rate Descriptive Statistics

Attribute	Value
Mean	68.21613
Standard Error	0.055781
Median	68
Mode	67
Standard Deviation	3.573445
Sample Variance	12.76951
Kurtosis	2.257995
Skewness	0.758252
Range	30
Minimum	56
Maximum	86

Supplemental textual data adds an extra perspective to the Information Overload phenomena; however its use in this experimental setting is problematic. The main reason for this is that there is no recorded data source (i.e. video material) which can precisely link the exact point in time when a participant had written the note down to the point in time when a particular experimental stimulus occurred. Although it is possible to speculate that the elicited stimulus occurred roughly at the time when the note writing was taking place or vice versa, this speculation could jeopardize the rigor of experimental design.

Table H.2: Common Textual Data Patterns

Pattern	Description
Missing details	Small pieces of information are missing in less than four columns.
Missing event	An entire event is not recorded on the textual
Illegible handwriting	Handwriting becomes illegible after an evident designed to induce information overload.
Fully completed	All items are completed in full. All essential pieces of information are recorded in full.
Strike-through	An entry is annulled with a line.
Incorrect names	A name or a set of names is spelled incorrectly after an IO stimulus.
Incorrect items	The item does not match the one specified by the system.
Incorrect time	The time for a specific attendee is noted incorrectly.
Incorrect note	The specified note is not related to the stimulus event.
Made-up information	The provided information is complete, but not related to the information presented on the screen.
Empty spaces	At least one column attribute is missing.
Change of writing style	Sudden change of writing style after an IO stimulus (i.e. switching from caps to cursive).
Symbolic annotations	Use of special symbols to annotate a change in item or to link two or more items together (i.e. arrows, stars, minuses).
Improper column use	An entry is placed in a wrong column (i.e. a food item is annotated in the time column).
Failure to complete	More than one entire event is completely missing from the notes.
Redundant information	One or more events are annotated two or more times.

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