Designing Attentive Information Dashboards with Eye Tracking Technology

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Abstract

With the use of Business Intelligence and Analytics (BI&A) systems, companies collect and analyze data from various sources to support data-driven decision making. In order to access BI&A systems, decision-makers leverage information dashboards, visual displays that arrange the most important information on a single screen. Despite the fact that information dashboards come with strong potentials to support better decision making, but they challenge their users' limited attentional resources by presenting huge amounts of information on one screen. Providing solutions addressing users' difficulties in managing limited attentional resources while working with information dashboards is an important research gap. Existing research in the Human-Computer Interaction (HCI) field highlights the importance of designing attentive user interfaces to assist users' attentional processes using eye tracking technology. This thesis builds upon the fields of HCI, Information Systems (IS) and psychology and follows the Design Science Research (DSR) methodology in order to answer the following research question: *"How to design attentive information dashboards for BI&A systems that enhance users' ability to manage attentional resources?"*.

Overall, five studies are performed in this thesis. In Study I, a systematic literature review on previous research focusing on eye-based interactive intelligent systems is conducted. As part of this study, a conceptual framework is developed, and future research directions are identified. Building on these results, three design cycles for designing attentive information dashboards are performed. The first design cycle includes two studies: Study II investigates attention problems of information dashboard users under consideration of their individual Working Memory Capacity (WMC). The results show that users with high and low WMC have different difficulties in managing their attentional resources. Study III evaluates different potential solutions for supporting data exploration tasks using eye movement data. The results show that providing feedback integrating real-time eye movement data supports users in managing their attentional resources better than general feedback with integrated off-line recordings of eye movement data. In the second design cycle, an attentive information dashboard for the data exploration task is designed and evaluated. In Study IV, theoretically grounded design principles are articulated, instantiated as a software artifact, and evaluated in a large-scale laboratory experiment. The results from analyzing the users' eye movement data reveal that the suggested design principles positively affect users' ability to manage limited attentional resources during data exploration tasks. In the third design cycle, attentive information dashboards with task resumption support are investigated. Study V instantiates three software artifacts using different gaze-based highlighting methods and evaluates them in a large-scale laboratory

experiment by considering short-term IT-mediated interruptions and the role WMC. The results demonstrate the need for personalization of such support under consideration of users' WMC.

This thesis contributes to the IS and HCI field by providing prescriptive knowledge in the form of nascent design theory for designing attentive information dashboards using eye tracking technology to enhance users' ability to manage limited attentional resources. The proposed attentive information dashboards are the first BI&A systems presented in the IS field that use real-time eye movement data for designing advanced built-in attention support functions. Also, practitioners can leverage the findings from this thesis for integrating attention support functionality into existing BI&A system supporting users in managing limited attentional resources.

Contents

List of Figures

List of Tables

List of Abbreviations

ANOVA	Analysis of Variance
AOI	Area Of Interest
AR	Augmented Reality
ARA	Attentional Resource Allocation
ARM	Attentional Resource Management
ASR	Attention Shift Rate
AUI	Attentive User Interface
BI	Business Intelligence
BI&A	Business Intelligence and Analytics
DP	Design Principle
DSR	Design Science Research
DSS	Decision Support Systems
EEG	Electroencephalography
EIS	Executive Information Systems
fMRI	Functional Magnetic Resonance Imaging
HCI	Human-Computer Interaction
HIP	Human Information Processing
IS	Information Systems
IIS	Interactive Intelligent Systems
MIS	Management Information Systems
MR	Meta-requirement
RQ	Research Question
RSR	Resumption Success Rate
SDK	Software Development Kit

SLR	Systematic Literature Review
TRS	Task Resumption Support
UI	User Interface
VAF	Visual Attention Feedback
VR	Virtual Reality
WMC	Working Memory Capacity

1. Introduction [1]

1.1. Motivation

Already in 1971, Herbert Simon pointed out that *"in an information-rich world, the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes ... it consumes the attention of its recipients".* (Simon, 1971, pp. 40-41). Following this idea, Goldhaber (1997) and Davenport and Beck (2001) have articulated the concept of *"attention economy"* emphasizing that human attention should be considered as a scarce commodity and should be treated as a new currency of business. When humans receive intensive information, they process it through a selective filter (Broadbent, 1958) which is considered as paying attention (Driver, 2001). Human attention is the core for perceptual and cognitive operations (Chun et al., 2011) and the reason for the selective processing of information is humans' limitation in attentional resources (Broadbent, 1958; Kahneman, 1973).

These days, the possibility to have instant access to huge amounts of information besides humans' limited attentional resources result in the battle of capturing users' attention by companies (Ahn et al., 2018; Hong et al., 2004b; Networks and PWC, 2016; Shen et al., 2015). According to the CEO of Microsoft, Satya Nadella: *"we are moving from a world where computing power was scarce to a place where it now is almost limitless, and where the true scarce commodity is increasingly human attention"* (Gausby, 2015, pp. 4). Recent studies show that the amount of time concentrating on a task before becoming distracted, decreased massively during the last years (Gausby, 2015; Statistics Brain, 2015). This means that these days users allocate their attention to tasks for only a short time and shift their attention rather fast. However, having proper attention allocation plays an important role in information processing and makes it possible to focus on the important information to pursue goals (Atkinson and Shiffrin, 1968; Wickens et al., 2016). Given this situation, supporting users in managing their limited attentional resources is one of the most pressing and difficult challenges in practice and research in today's information-rich world (Anderson et al., 2018; Bulling, 2016; Davern et al., 2012; Lerch and Harter, 2001).

With the use of big data technologies, organizations collect and analyze data from various resources to assist users in making better decisions (Günther et al., 2017). However, the path from data to decision is typically complex (Keim et al., 2008). Collecting data, extracting insights, and creating value is a challenging endeavor for companies and includes many activities. One essential activity is enabling decision-makers seamless access to data (Delen and Ram, 2018). A well-known class of Information Systems (IS) that supports such data-driven decisions are Business Intelligence and Analytics (BI&A) systems (Chen et al., 2012). As Figure 1.1 shows, the value chain of BI&A systems in companies can be organized in two stages. In the first stage, the collected raw data is transferred to insights by applying

[1] This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini et al. (2018c), Toreini et al. (2018b), Toreini and Langner (2019), Toreini et al. (2020b), Toreini et al. (2020c), Toreini and Maedche (2020), Toreini et al. (2020a)

different analytical techniques leveraging comprehensive BI&A infrastructures. This stage is critical since having high-quality insights is a foundation to make better decisions (Fink et al., 2017). Because of this capability, BI&A systems became a ubiquitous subject for companies' business performance and competitiveness in last years (Elbashir et al., 2008; Peters et al., 2016).

The second stage is extracting value from the provided insights by making proper decisions. The successful implementation of the underlying processes in this stage is the responsibility of human decision-makers. There is a need to empower them to leverage the extracted insights effectively with advanced interaction technologies. Human-Computer Interaction (HCI) field deals with developing interaction technologies and making the usage of systems effective (Preece et al., 2015). For BI&A systems, one prominent interaction technology is so-called information dashboards, which are increasingly popular forms of visualizing information (Behrisch et al., 2018; Pauwels et al., 2009; Preece et al., 2015; Yigitbasioglu and Velcu, 2012). Few (2006) has described information dashboards as *"visual displays of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance"*. Information dashboards are known as one of the most effective BI&A tools (Negash and Gray, 2008). They should be designed to present insights in a comprehensive way and be effective for decision-makers (Bačić and Fadlalla, 2016; Pauwels et al., 2009; Phillips-Wren et al., 2015; Yigitbasioglu and Velcu, 2012).

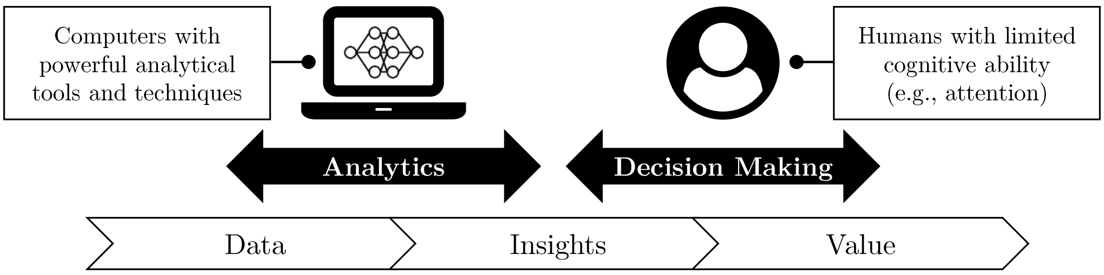


Figure 1.1.: Value chain of BI&A systems and the role of computers and humans.

Many BI&A systems fail to provide benefits to organizations because of improper design and usage of interaction technologies, including information dashboards (Deng and Chi, 2012; Schwarz et al., 2014; Trieu, 2017). In fact, the challenge for organizations is not to collect more information and derive insights as the first stage, but to use the information in an effective way as the second stage (Lerch and Harter, 2001). In this stage, users' cognition plays an important role while making business decision (Chen and Lee, 2003; Niu et al., 2013). However, humans have limited cognitive abilities (e.g., attention, working memory, etc.) that affect their performance while working with information dashboards (Davern et al., 2012; Lerch and Harter, 2001; Yigitbasioglu and Velcu, 2012). Extensive research on information visualization have shown that different types of charts could help to overcome human cognitive limitations (Dilla et al., 2010; Healey and Enns, 2012; Kelton et al., 2010), such as the limited capacity of attention and working memory (Haroz and Whitney, 2012). Both attention and working memory are known as a limited resource of humans, and they play an important role in information processing (Atkinson and Shiffrin, 1968; Wickens et al., 2016), constructing decisions (Orquin and Mueller Loose, 2013) and complex cognitive tasks, such as comprehension, reasoning, and problem-solving (Engle, 2002). Although providing visualized information is a practical approach for addressing these limitations (Borkin et al., 2016,1; Healey and Enns, 2012; Somervell et al., 2002; Ward et al., 2010), presenting several charts on one screen in the form of an information dashboard can rechallenge the boundaries of cognitive resources such as allocation of attentional resources (Toreini and Langner, 2019). The allocation of attentional resources is the set of processes enabling and guiding the selection of incoming perceptual information (Eriksen and Yeh, 1985). Understanding different information is strongly limited to the selection of attended locations (Itti and Koch, 2001; March and Shapira, 1987). Therefore, proper allocation of attentional resources is necessary to analyze business insights while processing information dashboards (Lerch and Harter, 2001; Singh, 1998). Thus, information dashboards should consider users' cognitive limitations in their design and functional features. However, existing research on BI&A systems is limited to their business significance and widespread use and providing solutions regarding corresponding users' cognitive challenges while working with BI&A systems is a research gap (Browne and Parsons, 2012; Chen and Lee, 2003; Davern et al., 2012; Niu et al., 2013). Several researchers have suggested a synergistic collaboration of BI&A and HCI to find efficient solutions for handling the huge amount of collected data (Chen et al., 2012; Holzinger, 2013; Keim et al., 2008).

Users' eye movements have been shown to provide insights into users' cognitive process (Hayhoe and Ballard, 2005; Liversedge and Findlay, 2000; Rayner, 1998). More recently, eye tracking technology usage increased considerably in different research areas primarily because of the availability of cheaper, faster, more accurate, and easier to use eye trackers (Duchowski, 2017). In general, Duchowski (2002) has broadly categorized eye tracking applications into the classes of diagnostic and interactive. Researchers use eye tracking technology to provide quantitative evidence of the user's cognitive processes in diagnostic applications. Diagnostic eye tracking applications collect user's eye movement data while doing a task, and later, researchers use these off-line records for the evaluation. The second category comprises interactive eye tracking applications that interact with the user based on observed eye movement data. In this case, the system uses the user's eye movement data in real-time and enables eye-based interactions. The off-line mode used for diagnostic purposes has been the most well-known usage scenario of eye trackers and researchers have intensively used it in various fields (Jacob and Karn, 2003; Lai et al., 2013; Sharafi et al., 2015; Tien et al., 2014; Wedel and Pieters, 2008). This usage is popular since it provides objective data about users, which is complementary to subjective self-reported data (Dimoka et al., 2012). Also, eye tracking has been extended in IS research with the primary focus on understanding users visual behaviour and the diagnostic usage (Dimoka et al., 2012; Riedl et al., 2017).

Furthermore, with the advancement of eye tracking technology during the last years, researchers have increasingly leveraged the possibility of collecting and processing user eye movement data in real-time. The real-time mode has created new opportunities for researchers beyond the off-line mode by actively involving the user in an interactive system, deriving cognitive dimensions and building intelligent systems that are sensitive to the cognition of the user (Bulling and Gellersen, 2010; Bulling et al., 2011). Jameson and Riedl (2011) introduce Interactive Intelligent Systems (IIS) as systems that focus on intelligent technology and user interactions. I consider systems that integrate users' eye movement data in real-time to design IIS as eye-based IIS. The integration of real-time eye movement data as input for designing eye-based IIS has grown during the last years (Chuang et al., 2019; Nakano et al., 2016). The primary usage of the eye movement data in real-time is to track users' attention (Carrasco, 2011; Kowler, 2011). In the HCI field, an eye-based IIS that is sensitive to users' attention and assist them in attentional processes is called Attentive User Interface (AUI) (Bulling, 2016; Roda and Thomas, 2006; Vertegaal, 2003). The research on AUIs arose from the idea that processing huge amounts of information surrounding users is difficult since their attention is a limited resource (Anderson et al., 2018; Bulling, 2016). The need for designing AUIs is emphasized by HCI researchers during last years (Anderson et al., 2018; Bailey and Konstan, 2006; Bulling, 2016; Roda, 2011; Roda and Thomas, 2006). Furthermore, the users' eye movement data is considered as the primary data source for designing AUIs (Bulling, 2016; Majaranta and Bulling, 2014; Roda and Thomas, 2006).

IS researchers also have suggested using eye movement data to design innovative IS applications that enhance users' capability (Davis et al., 2014; Dimoka et al., 2012; Maglio et al., 2000; Riedl and Léger, 2016; vom Brocke et al., 2013). In BI&A field, the usage of eye tracking technology was limited to diagnostic purposes so far (Kurzhals et al., 2016). However, researchers have called for integrating eye tracking technology to BI&A systems and design innovative features that support decision-makers while using these systems based on real-time eye movement data (Silva et al., 2019). Therefore, in this thesis, I focus on closing this gap by designing innovative information dashboards using eye tracking technology as **Attentive Information Dashboards**. I define the term attentive information dashboard as follows:

> *"An information dashboard that is sensitive to the decision-makers' attention and supports managing limited attentional resources".*

Based on this definition and depicted in Figure 1.2, an attentive information dashboard has two major components that include sensory and attention support. First, the sensory component focuses on making the dashboard sensitive to the users' attention. To reach this goal, I developed a system to track users' eye movement data by integrating a low-cost desktop-mounted eye tracker (Farnsworth, 2019), Tobii 4C eye tracker. Collecting, analyzing, and activating attention support features are the three key steps in this component.

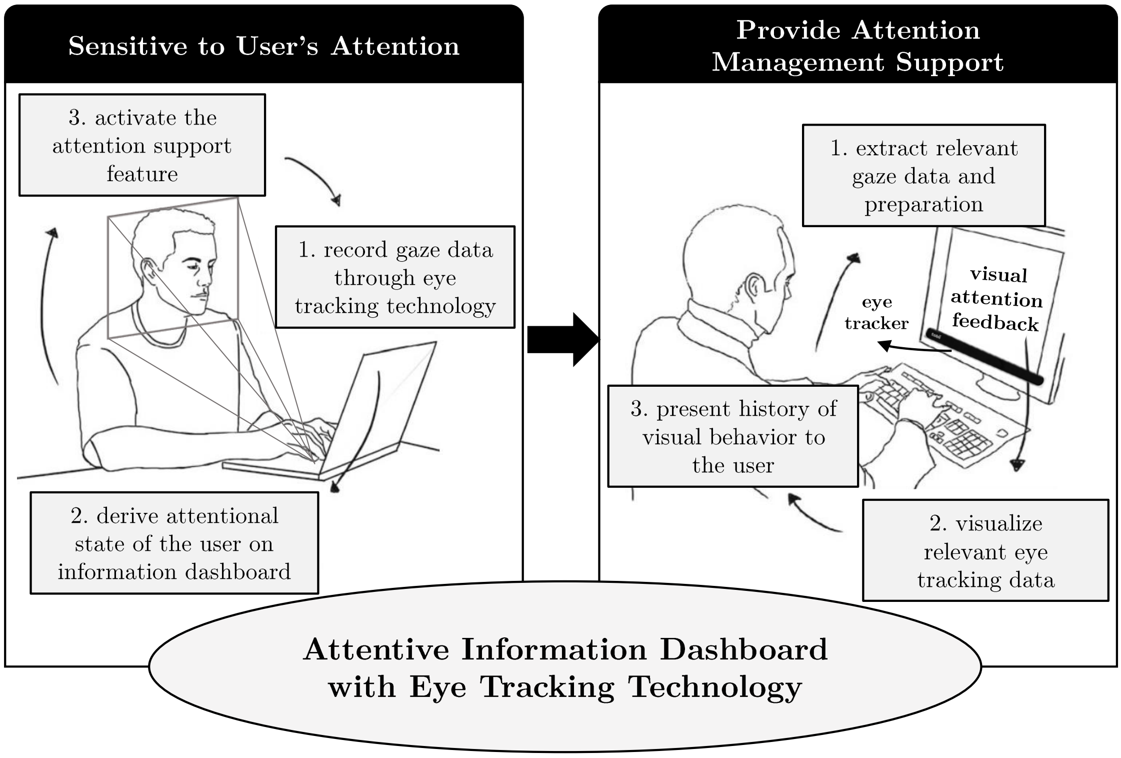


Figure 1.2.: Major components of attentive information dashboards (Figure is adapted from Riedl and Léger (2016)).

The attention support component focuses on assisting information dashboard users in managing their limited attentional resources in different situations. Such assistants can be done by adapting the system automatically (e.g, (Buscher et al., 2012; Ishii et al., 2013; Maglio et al., 2000)), or increasing the users' self-awareness about attentional challenges (e.g., (D'Angelo and Gergle, 2018; Kern et al., 2010; Mariakakis et al., 2015)). Users need to scan complex displays systematically to extract the relevant information (Proctor and Vu, 2006). However, users of decision support systems have difficulty remembering activities that have been accomplished and need cognitive aids to remind them (Singh, 1998). Also, general research shows that users have difficulty to recall what they saw, where they looked and in what order (Dimoka et al., 2012). This situation can results in missing information on information dashboards during data exploration tasks. Providing users with feedback during interacting with UIs is known as one of the most basic and important usability principles (Nielsen, 1993). Preece et al. (2015, p.26) have described feedback as *"sending back information about what action has been done and what has been accomplished while allowing the person to continue with the activity".* Various feedback types are available in digital environments for assisting users in accomplishing their tasks (Morana et al., 2017). One of them is cognitive feedback that presents information about user's cognitive strategy (Lim et al., 2005; Nah and Benbasat, 2004). Prior studies have shown the benefit of using cognitive feedback for users to do their tasks (Balzer et al., 1989; Nah and Benbasat, 2004; Sengupta and Te'eni, 1993). Also, providing feedback about users' attention using eye tracking technology has shown positive effects in information processing (e.g., (D'Mello et al., 2012; Qvarfordt et al., 2010; Sharma et al., 2016)). Therefore, as the attention support component, I propose providing feedback on how users visually explore information dashboards. I name this type of feedback as individualized **Visual Attention Feedback (**VAF) and define it as:

> *"A type of feedback that leverages users' real-time eye movement data to increase their awareness about the previous attentional resource allocation".*

This type of feedback is a self-tracking feature and has the aim to increase users' awareness. Self-tracking techniques support gaining self-knowledge about own behaviors and habits and are becoming an emerging trend (Choe et al., 2014; Lupton, 2016; Rivera-Pelayo et al., 2017). However, there is a lack of evidence on how such techniques can influence the users' performance in workplaces (Rivera-Pelayo et al., 2017). Furthermore, there is limited research on using eye movement data as self-tracking feedback for IS applications (Lux et al., 2018). In this thesis, I focus mainly on providing individualized VAF to increase users' self-awareness for two situations that users have difficulty in managing their limited attentional resources: data exploration and resuming interrupted tasks.

First, the individualized VAF focuses on supporting data exploration tasks and avoiding missing important information. The users' tasks with information dashboards can be distinguished into search tasks and data exploration tasks (Vandenbosch and Huff, 1997). In a search task, the user seeks answers to specific questions. In data exploration tasks, the user browses the dashboard generally to get a comprehensive understanding of the current status. In this case, the user examines data without having prior understanding of what information it might contain (Baker et al., 2009). Gartner–Magic Quadrant for BI&A has emphasized that well-designed information dashboards that enable the exploration of data and support proper decision making as a critical capability of BI&A systems (Sallam et al., 2017). However, even with a well-designed dashboard, exploring the compressed amount of visualized information is challenging for users (Baskett et al., 2008; Figl and Laue, 2011; Haroz and Whitney, 2012; Healey and Enns, 2012; Sedig and Pasob, 2013). Particularly, information dashboards have the potential to create difficulties in managing attentional resources since users can only focus on a limited set of information and can miss other parts while exploring the information dashboard (Alberts, 2017; Dilla et al., 2010; Lurie and Mason, 2007). Such a task competes for the decision-maker's attentional resources (Lerch and Harter, 2001).

Second, the VAF focuses on supporting the users' difficulty in resuming an interrupted task. The interest in BI&A systems has increased in recent years because of the opportunities associated with data and analysis (Chen et al., 2012) and the increased usage of data-driven decision making. Meanwhile, these days the workplace is accompanied by frequent interruptions of task execution (Czerwinski et al., 2004; Mark et al., 2008). For example, operational dashboards are used to monitor the process execution in manufacturing in real-time, while interruptions can negatively affect their performance. Interruptions are known to have various negative impacts, such as higher task completion time, the number of errors, or anxiety in multitasking situations (Addas and Pinsonneault, 2015; Borst et al., 2015; Czerwinski et al., 2004; Gillie and Broadbent, 1989). Also, in the workplaces, the increasing number of interruptions affect decision-makers' primary task performance (Galluch et al., 2015; Gupta et al., 2013; Ou and Davison, 2011). Employees have difficulty resuming their primary task after an interruption and having delay getting back on the task (Hemp, 2009; Mark et al., 2005). Even though task disruptions can sometimes be unavoidable, e.g., due to the importance of the secondary task or the specific context of work (Dostal et al., 2013), it is necessary to design systems that provide advanced support in better interruption management (Anderson et al., 2018; Bailey and Konstan, 2006). Leveraging such systems to detect an interruption and provide Task Resumption Support (TRS) by highlighting previously attended areas have seen to be supportive for users in task resumption (Göbel and Kiefer, 2019; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). A promising approach to provide TRS is using eye tracking technology. This technology tracks the user's eye movements to understand the moment of task switching and subsequently visualize the user's eye movement data as an indicator of the most recent area of attention (Dostal et al., 2013; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). Gaze-based TRS makes previous cognitive processes more explicit by providing memory aids. It gives hints to the users to remember what they were thinking or what might have been their intention before shifting to the interruption task (Majaranta and Bulling, 2014).

In summary, in this thesis, I deliver an innovative solution (attentive information dashboards with individualized VAF) for a real-world problem (managing limited attentional resources) following the Design Science Research (DSR) methodology. DSR has the aim to solve significant social or organizational problems by designing artifacts (Hevner et al., 2004). The challenges and strategies of designing attentive information dashboards and individualized VAF are described as Research Questions (RQs) in the subsequent section.

1.2. Research Gaps and Associated Research Questions

With this thesis, I explore designing attentive information dashboards and support users in managing their limited attentional resources in different situations. Therefore, I focus on answering the following main RQ in this thesis:

> ***Main RQ:*** *How to design attentive information dashboards for* BI&A systems that enhance users' ability to manage attentional resources?

To answer the main RQ step-by-step, I defined five sub-RQs can be seen in Figure 1.3. Next, I designed and executed five studies to address each sub-RQs. In the following, I present the research gaps and the assigned sub-RQs that are covered in this thesis.

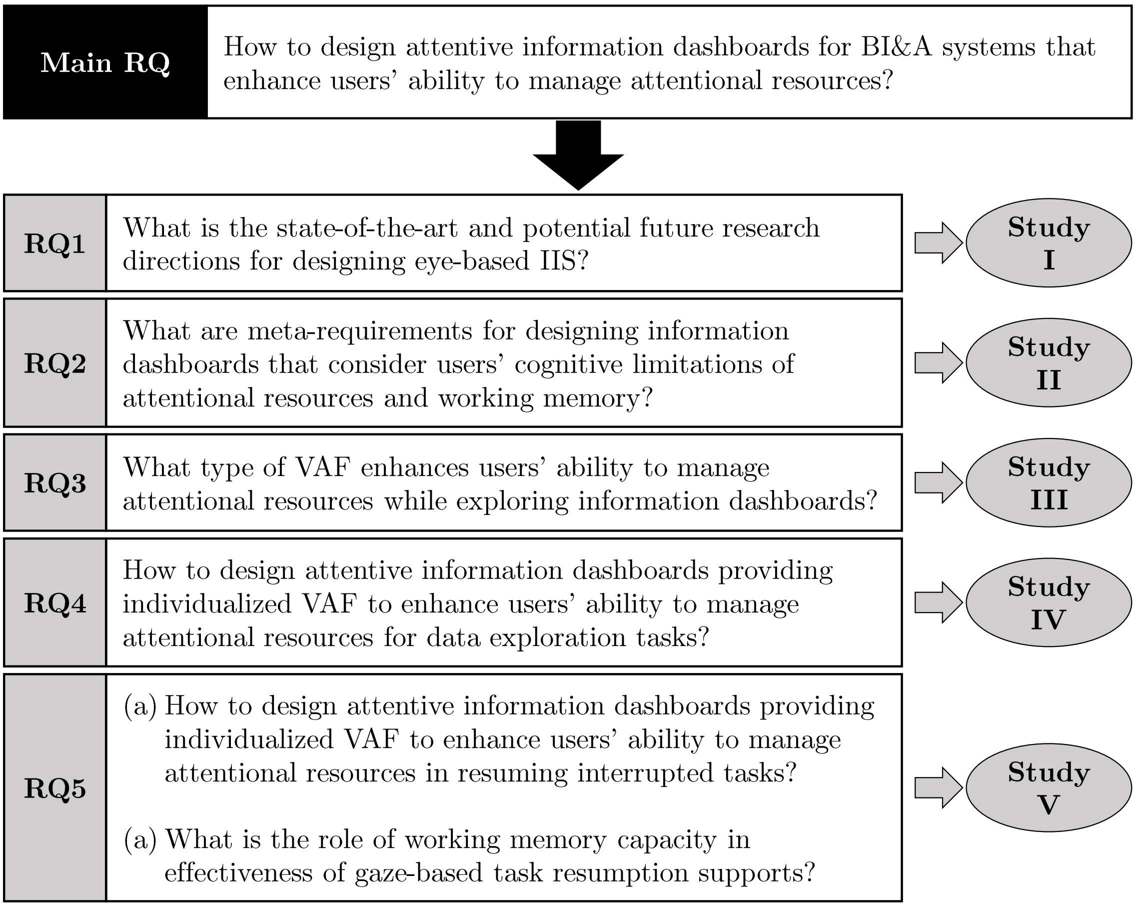


Figure 1.3.: Overview of research questions addressed in this thesis.

The **first RQ** deals with state-of-the-art and possible future research directions in using eye tracking technology for designing IIS in general. Although the number of research studies focusing on eye-based IIS increased during the last years (Chuang et al., 2019; Nakano et al., 2016), there is a lack of common understanding of this class of systems. The current eye tracking literature reviews focus mainly on summarizing the usage of eye trackers in specific fields concentrate on diagnostic or interactive purposes (Duchowski, 2002; Jacob and Karn, 2003) rather than integrating real-time eye movement data for designing IIS. For example, Velloso and Carter (2016) presented the review of gaze-based interaction systems in gaming, Sharafi et al. (2015) discussed the advantages of eye tracking for software engineering, Tien et al. (2014) discussed the role of eye tracking technology in medical research, Lai et al. (2013) presented how eye tracking technology can be used to describe the process of learning, Rosch and Vogel-Walcutt (2013) presented the implementation of eye tracking into training environments, Wedel and Pieters (2008) discussed the usage of eye tracking technology in marketing, and Vasseur et al. (2019) presented the review of using eye tracking in IS field. To the best of my knowledge, summarizing existing research in using real-time eye movement data for designing eye-based IIS (e.g. AUIs) is a research gap. Therefore, as the first step, this thesis focuses on closing this gap by answering the following RQ in **Study I**:

> ***RQ1:*** *What is the state-of-the-art and potential future research directions for designing eye-based IIS?*

I addressed this RQ by conducting a Systematic Literature Review (SLR) study and identifying the state-of-the-art in eye-based IIS field. Based on this analysis, I provide a list of future research directions.

The **second RQ** deals with identifying attentional problems when users explore information dashboards and derive Meta-requirements (MRs) for designing innovative information dashboards. Visualized information supports users to process huge amounts of information by overcoming their limitations in attentional resources and working memory (Borkin et al., 2013; Healey and Enns, 2012; Somervell et al., 2002; Ward et al., 2010), but it is not clear how they play a role while exploring information dashboards. Few studies have addressed users' attentional challenges while working with information dashboards (Alberts, 2017). The primary focus is to evaluate the design features (e.g., presentation formats, colors, size, etc.) and their impact on users' attention (Bera, 2014,1; Burch et al., 2011; Nadj et al., 2020) rather than users difficulties in managing limited attentional resources. It is important since to analyze business insights; it is necessary to have proper allocation of attentional resources (Lerch and Harter, 2001; Singh, 1998). Understanding different information objects is strongly limited to the selection of attended locations (Itti and Koch, 2001; March and Shapira, 1987) and attention processes play an active role in constructing decisions (Einhorn and Hogarth, 1981; Orquin and Mueller Loose, 2013). Besides, it has been studied how individual user characteristics such as working memory impact the effectiveness of visualization techniques (Steichen et al., 2013; Toker et al., 2013), but again this individual characteristic is not investigated during information dashboards exploration. Designing effective supports requires a detailed understanding of the underlying cognitive processes (Lerch and Harter, 2001). Cognitive limitations and related errors are among under-researched topics in the IS field, and there is a general need for more research on that (Browne and Parsons, 2012). Also, few researchers have examined BI&A systems and users' cognitive limitations (Davern et al., 2012; Niu et al., 2013). Particularly, researchers have emphasized the need to study individual cognitive limitations on the effectiveness of information dashboards (Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). Using eye tracking technology to assess the impact of systems on users' information processing capacity is considered as a research opportunity by IS researchers (Dimoka et al., 2012). Therefore, I focused on closing this research gap by comparing how individuals with different Working Memory Capacity (WMC) allocate their attentional resources during data exploration tasks. With this focus, I aim to find MRs for designing attentive information dashboards by addressing the following RQ in **Study II**:

> ***RQ2:*** *What are meta-requirements for designing dashboards that consider users' cognitive limitations of attentional resources and working memory?*

I addressed this RQ by conducting an exploratory study using eye tracking technology for diagnostic purposes to explore the impact of attention and working memory limitations on the effectiveness of information dashboards.

The results from RQ2 highlight the user challenges in managing limited attentional resources while exploring information dashboards. Therefore, the **third** RQ deals with examining different solutions to support managing attentional resources with the usage of eye tracking technology. The results from RQ1 show the user adaptation approach's effectiveness by increasing users' awareness of previous visual behavior. Furthermore, the results show a trend in using this approach by applying low-cost eye tracking technology. Maglio et al. (2000) have suggested observing user behavior through multiple resources, including eye tracking technology and adapting IS applications by displaying relevant information to the user. However, the usage of eye movement data for designing feedback and increase users-awareness is a research gap (Lux et al., 2018). Such awareness can be either delivered by the usage of off-line records of eye movement data from the users that accomplished the same task previously (e.g., (Sridharan et al., 2012)) or by using users' real-time eye movement data (e.g., (Qvarfordt et al., 2010)). Although eye tracking is the dominant tool for IS studies that integrate neuroscience tools (Riedl et al., 2017), the results from RQ1 show a lack of research on integrating real-time data for designing innovative IS applications. Furthermore, off-line recordings are mainly used to support designers in understanding users' behavior and improving the design rather than supporting users by providing them as VAF. Both using eye movements from previous users and using real-time eye movement data for designing support features in BI&A systems are suggested by researchers in the intersection between BI&A and eye tracking field (Silva et al., 2019). Also, IS researchers have called for the usage of eye tracking technology to design innovative IS applications that enhance users' capability (Davis et al., 2014; Dimoka et al., 2012; Riedl and Léger, 2016; vom Brocke et al., 2013). However, best of my knowledge, none of these techniques is investigated so far. Therefore, I focus on closing this research gap by addressing the following RQ in **Study III**:

> ***RQ3:*** *What type of VAF enhances users' ability to manage attentional resources while exploring information dashboards?*

I addressed this RQ by conducting an eye tracking pilot study for comparing three different types of VAF (one real-time usage and two off-line usages of eye movement data) and their impact on managing limited attentional resources during data exploration tasks.

The **fourth RQ** deals with designing attentive information dashboards for data exploration tasks. Such a task competes for the decision-maker's attentional resources (Lerch and Harter, 2001). Also, findings from RQ2 highlights users' challenges in managing limited attentional resources of users when performing the data exploration task. By answering RQ3, the initial findings indicated that using real-time eye movement data for individualized VAF works better than off-line eye movement data as general VAF types. Therefore, in a subsequent study, I investigate the design of individualized VAF and its influence on data exploration tasks in more detail. Previous studies in other fields have shown the positive impacts of individualized VAF as a self-tracking feature on managing attentional resources (Deza et al., 2017; D'Mello et al., 2012; Göbel and Kiefer, 2019; Qvarfordt et al., 2010; Sharma et al., 2016; van Gog et al., 2009). Although using eye tracking technology is popular among IS researchers (Riedl et al., 2017), no study has examined using eye movement data for designing individualized VAF (Lux et al., 2018). Furthermore, researchers have suggested to integrate eye trackers for designing supportive features for BI&A users (Silva et al., 2019). Therefore, there is a lack of knowledge on how to design individualized VAF and what is its effect on users of information dashboards. To close this gap, I addressed the following RQ in **Study IV**:

> ***RQ4:*** *How to design attentive dashboards providing individualized VAF to enhance users' ability to manage attentional resources for data exploration tasks?*

I addressed this RQ by comparing the effects of individualized VAF with the condition that users did receive a general text-based explanation as VAF in a large-scale laboratory eye tracking study.

The **fifth RQ** deals with providing attentive information dashboards with TRS. The results from RQ2 highlighted user's difficulty in resuming an interrupted task. Previous studies also show that the workplace is also accompanied by frequent interruptions of task execution (Czerwinski et al., 2004; Mark et al., 2008) and employees have have a long delay in getting back to the primary task after interruptions (Hemp, 2009; Mark et al., 2005). The results from RQ1 reveal that existing TRS features integrated with eye trackers are not investigated in workplaces. Also, Anderson et al. (2018) have noted the necessity to design systems that provide advanced support in better managing interruptions. Therefore, as another type of individualized VAF, I decided to leverage eye tracking to provide TRS for information dashboard users. Previous studies have used eye tracking technology to collect and then visualize the user's eye movement data as an indicator of the most recent area of attention after resuming an interrupted task (Dostal et al., 2013; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). As the results from RQ1 shows, existing gaze-based TRS systems mainly focused on reading tasks. No research has investigated providing such support for performing data exploration tasks on information dashboards. Therefore, there is a lack of knowledge on how to design it and its effect on users of information dashboards. To close this gap, I addressed the following RQ in **Study V**:

> ***RQ5a:*** *How to design attentive information dashboards providing individualized VAF to enhance users' ability to manage attentional resources in resuming interrupted tasks?*

Besides, previous studies have shown that user characteristics such as WMC play an essential role in managing interruptions (Cane et al., 2012; Foroughi et al., 2016; Mark et al., 2008; Ratwani and Trafton, 2008; Werner et al., 2011). Also, theoretical frameworks about interruption emphasize the role of working memory in handling interruptions (Altmann and Trafton, 2002; Borst et al., 2015). Users with higher WMC can better remember their previous visual behavior and thus better deal with task resumptions. Moreover, it is considered as an essential individual characteristic while users are working with visualized information such as on information dashboards (Haroz and Whitney, 2012; Healey and Enns, 2012; Toker et al., 2013). Also, the findings from RQ2 suggest designing VAF types that fit users WMC. However, reviewing gaze-based TRS studies collected in RQ1, highlights that the impact of gaze-based TRS under consideration of WMC is a research gap. There is a need for further research on how to present TRS to the user based on their individual characteristics (Anderson et al., 2018). To close this gap, I addressed the following RQ in **Study V** as well:

> ***RQ5b:*** *What is the role of working memory capacity in effectiveness of gaze-based task resumption supports?*

Therefore, in this study, I focus on designing and understanding the impact of different highlighting methods for gaze-based TRS (last point, heatmap, scanpath) under consideration of a specific task and a specific user characteristic.

1.3. Thesis Structure

Figure 1.4 presents an overview of this thesis with 9 chapters. **Chapter 1** motivates the topic and provides an overview of the entire thesis. In **Chapter 2**, I first present the conceptual foundations relevant to this thesis including attention, working memory, and human information processing theory. Additionally, I present related work studies relevant to this thesis including eye tracking technology, AUI, BI&A systems, and information dashboards. Subsequently, I address the first RQ in **Chapter 3** as Study I. In this chapter, I first present a conceptual framework for the systems that integrate real-time usage of eye movement data to develop innovative interaction, considered as eye-based IIS. Later, I summarize existing knowledge in this field by conducting a SLR study. Moreover, I provide a list of future research directions for eye-based IIS as an outcome of this analysis. Later in **Chapter 4**, I introduce the research methodology of the entire DSR project with three design cycles that were investigated in each chapter of this thesis.

Chapter 5 presents the results from the first design cycle. This design cycle includes two studies addressing RQ2 (Study II) and RQ3 (Study III). In Study II of this thesis, I addressed RQ2 by conducting an exploratory study using eye tracking technology and investigated the impact of attention and working memory limitations on the effectiveness of information dashboards. This study's results highlight the need to design attentive information dashboards to support users in managing their limited attentional resources during data exploration and task resumption after an interruption. Therefore, I articulated initial MRs for designing attentive information dashboards. In the Study III of this thesis, I addressed RQ3 by designing three types of VAF (two based on off-line eye movement data and one based on real-time eye movement data) and conducted an eye tracking pilot study to evaluate their effectiveness. The results highlight that an individualized VAF using gaze data in real-time supports users in a better way compared to other VAF types.

Chapter 6 presents the results from the second design cycle, which addresses RQ4 (Study IV). In this design cycle, I articulate theoretically grounded Design Principles (DPs) and instantiate a software artifact leveraging users' eye movement data in real-time to provide attentive information dashboards that support data exploration with individualized VAF. Later, I evaluated the instantiated software artifact in a large-scale laboratory experiment with 92 participants as a suggested method to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012). Analysis of users' eye movements reveals that the suggested DPs have a positive effect on enhancing users' ability to manage attentional resources.

Chapter 7 present the results of the third design cycle, which addresses RQ5 (Study V). In this design cycle, I propose attentive information dashboards that support users in resuming an interrupted task. Eye trackers are a promising technology to provide TRS using gaze-based highlighting methods. Consequently, with gaze-based TRS as individualized VAF, users are reminded regarding their previous visual behavior and assisted in resuming the primary task more efficiently in case of interruptions. In this design cycle, I first present dimensions that impact designing effective gaze-based TRS by analyzing previous research in the field of interruption and gaze-based TRS. Next, I articulated theoretically grounded DPs and instantiate a software artifact leveraging users' eye movement data in real-time to provide attentive information dashboards with three types of gaze-based TRS. Later, I evaluated three gaze-based highlighting methods (last point, heatmap, scanpath) after a short-term IT-mediated interruption (Addas and Pinsonneault, 2015) in an eye tracking study (N=48) and compared their effectiveness based on users' WMC. The results suggest that the need for gaze-based TRS types is different for users with high and low WMC. Notably, the heatmap highlighting method is supportive for low WMC users, while users with high WMC may not need gaze-based TRS for short-term IT-mediated interruptions.

Chapter 8 presents the theoretical and practical contributions of this thesis. Moreover, I present the prescriptive knowledge created in this DSR project in the form of a nascent design theory. I also discuss the knowledge contribution of this DSR project according to the DSR knowledge contribution framework by Gregor and Hevner (2013). Furthermore, I present the limitation of this thesis and provide future research suggestions. Finally, in **Chapter 9**, I conclude the thesis.

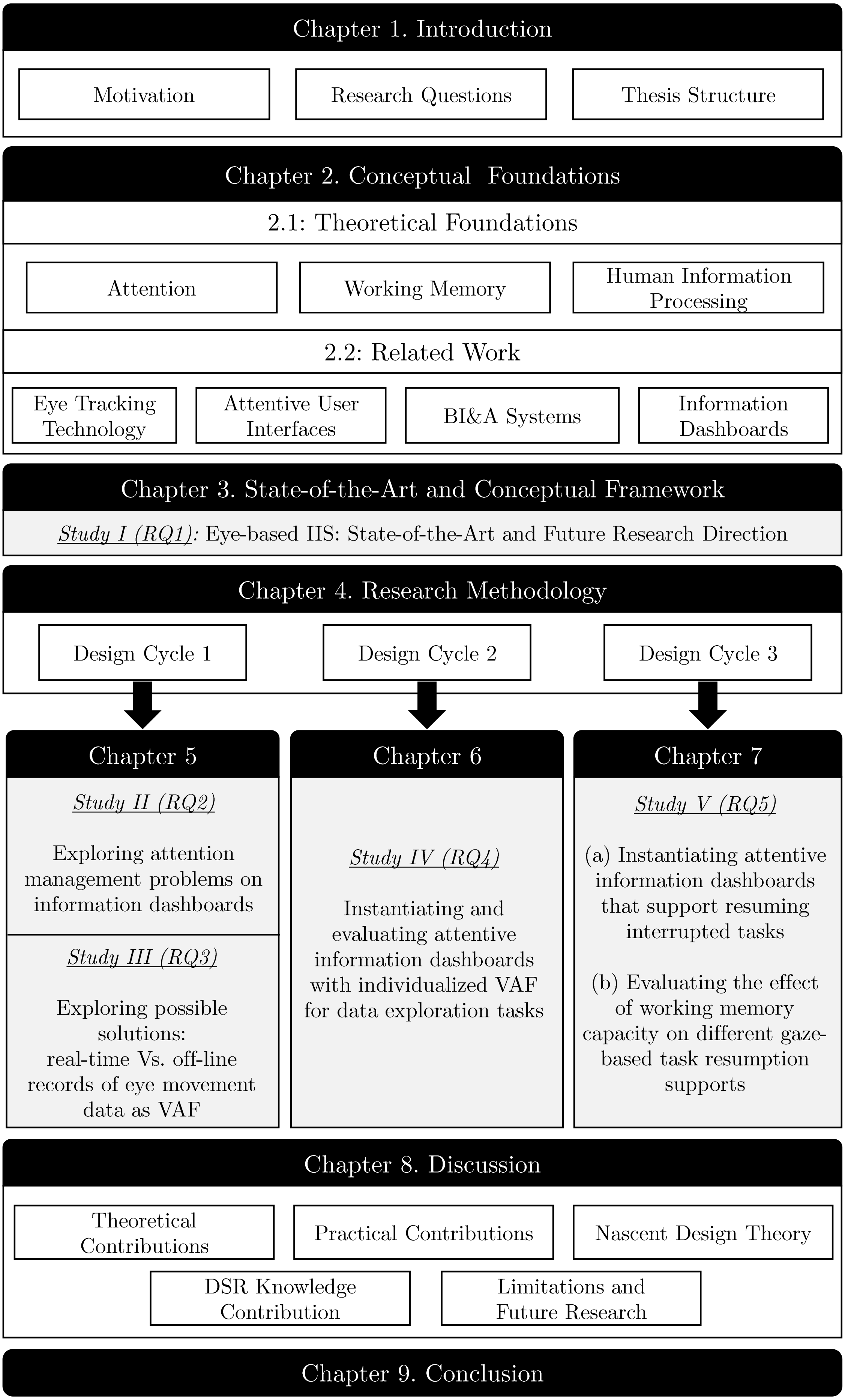


Figure 1.4.: Structure of the thesis.

2. Conceptual Foundations [1]

2.1. Overview

In this thesis, I focus on the intersection between research streams in three fields of studies, including Human-Computer Interaction (HCI), Psychology, and Information Systems (IS). Figure 2.1 presents an overview of the relevant research streams with selected example studies. Furthermore, the research gaps introduced in Section 1.2 are positioned within these research streams.

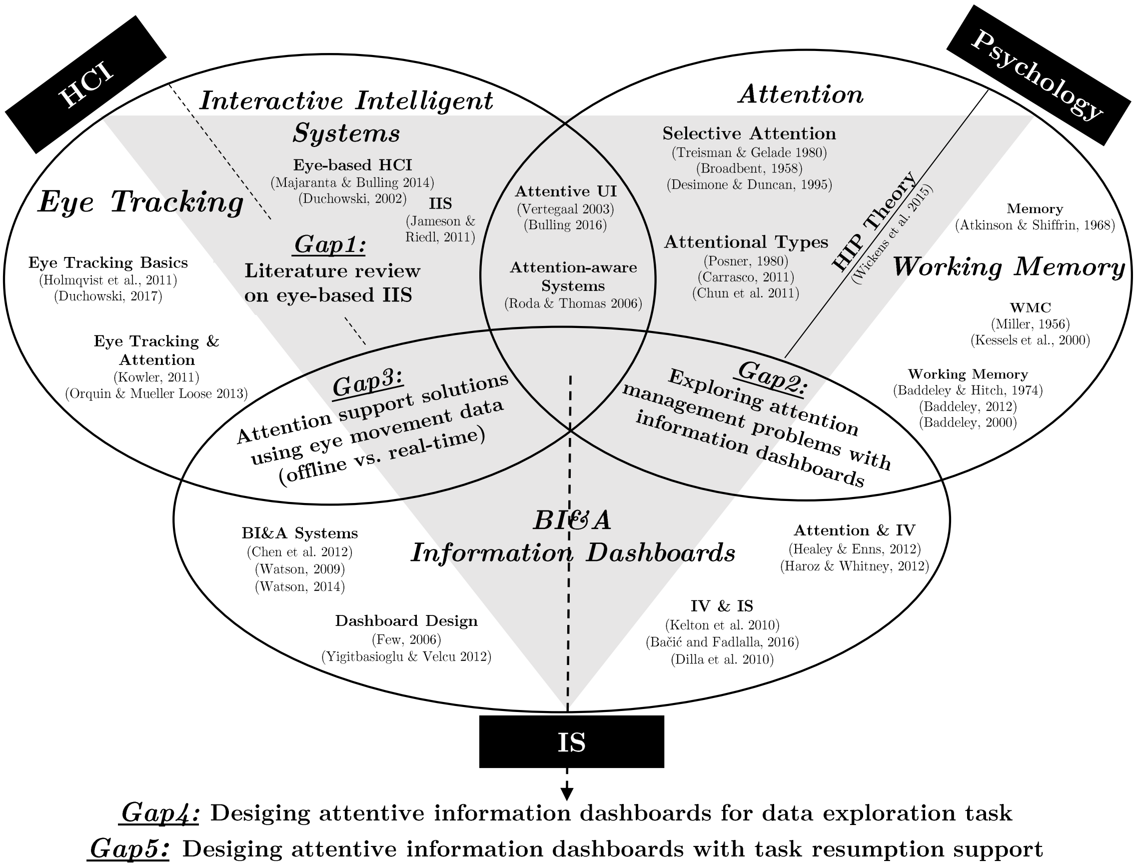


Figure 2.1.: Overview of research streams, theoretical foundations and research gaps.

From the **HCI** perspective, this thesis covers the two research streams including eye tracking technology and IIS. IIS are intelligent systems that people interact with and they emphasize the interplay of intelligent technology with advanced interactions of users (Jameson and Riedl, 2011). The first research gap is positioned at the intersection of these two research streams as eye-based IIS. In this thesis, I mainly focus on a specific type of eye-based IIS that is sensitive to users' attention and aims to support their attentional process, called Attentive User Interface (AUI). From the **Psychology** perspective, I investigate the role of attention and working memory, which play an essential role in

[1] This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini et al. (2018c), Toreini et al. (2018b), Toreini and Langner (2019), Toreini et al. (2020b), Toreini et al. (2020c), Toreini and Maedche (2020), Toreini et al. (2020a)

Human Information Processing (HIP) theory. Finally, from the **IS** perspective, I investigate the role of BI&A systems and information dashboards as a specific component of BI&A systems. The second research gap focuses on the intersection between information dashboards and the psychological constructs of attention and working memory. The third research gap addresses the intersection between information dashboards and the type of eye-based IIS, especially by comparing the real-time and off-line usage of eye movement data to support information dashboard users' attentional process. Furthermore, the fourth and fifth research gaps address the intersection between all three aspects by investigating how to design attentive information dashboards and individualized VAF to support data exploration tasks and resuming interrupted tasks.

In the following, I first describe the relevant theoretical foundations used in this thesis. After that, I outline existing studies within each research stream as related work.

2.2. Theoretical Foundations

2.2.1. Attention

Following the APA dictionary of psychology [2], attention is discussed as *"state in which cognitive resources are focused on certain aspects of the environment rather than on others and the central nervous system is in a state of readiness to respond to stimuli"*. However, researchers do not offer a dedicated definition for attention in research area (Anderson et al., 2018) and consider it rather generally as selective processing of incoming sensory information (Driver, 2001). The reason for emphasizing on selective processing is humans' limited attentional resources (Chun et al., 2011). Selective attention initially has been introduced as part of Broadbent's filter theory (Broadbent, 1958). It argues that when humans' perceptual system is overwhelmed by information overload, it starts to process the information through a selective filter. The limited capacity of attentional resources is not fixed and can vary based on different conditions such as task and user's characteristic (Kahneman, 1973). An easy task requires little attention, and a difficult task demands more attentional resources. Furthermore, users with different expertise can have different capacities.

One can differentiate attention in goal-directed and stimuli-driven attention as well as covert and overt attention (Desimone and Duncan, 1995). Goal-directed attention is the voluntary type of attention, whereas stimulus-driven attention is involuntary (Corbetta and Shulman, 2002). Researchers consider goal-directed attention as selective attention that is due to the limited attentional resources of humans. In this case, users select stimuli to allocate attention consciously and based on their intention. Additionally, they refer to stimuli-driven attention when external stimuli capture the user's attention unconsciously. Color, orientation, size, motion, depth, etc. are known as guiding representation that involuntary lead users' attention to salient objects (Wolfe and Horowitz, 2004). Treisman and Gelade (1980) discussed these elements and the role of them as *" Feature-Integration Theory of Attention"*. Figure 2.2 shows an example of the two different types of attention.

[2] https://dictionary.apa.org/attention

In this example, the users are asked to find the IISM logo among four existing logos. On the left side, they control the attention voluntarily and guide it to do the task by finding the IISM logo on the bottom-right position. However, in the right side example, changing the brightness of the four logos leads to attracting users' attention to the logo on the top-right first (KIT logo), while they do not have control over their attention allocation. That takes a while to overcome this and shift attention and achieve the goal of finding the IISM logo.

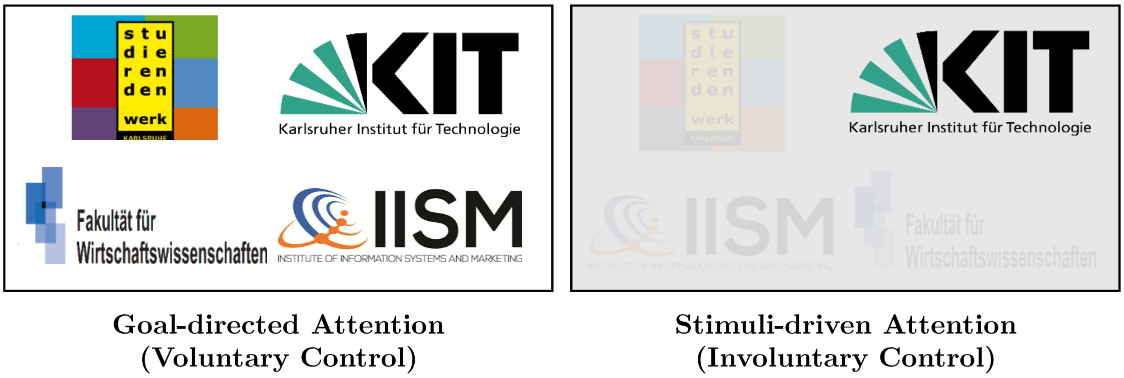


Figure 2.2.: An example of goal-directed and stimuli driven attention. In both pictures the user has the task to find the IISM logo.

Furthermore, Posner (1980) has distinguished overt and covert attention as two other categories of attention. Overt attention is an extrinsic behavior and aids humans to monitor the environment. Also, overt attention guides the users' head-turning and eye movements to an object (Carrasco, 2011). Researchers measured the users' overt attention by using eye tracking technology in previous studies (Kowler, 2011). Just and Carpenter (1980) have proposed the eye-mind assumption that describes the relationship between the pattern of eye movements and the underlying cognitive processes. Based on this assumption, where users are fixating dedicates their overt attention. Also, both goal-directed and stimuli-driven attention control user's eye movements (Orquin and Mueller Loose, 2013). As the other attention type, the covert attention is an inward activity in which the brain attends to an object without any extrinsic behavior. This attention type influences the brain signals. Researchers measure it by leveraging neuroscience tools such as Electroencephalography (EEG) and Functional Magnetic Resonance Imaging (fMRI). Figure 2.3 shows an example of overt and covert attention. In the overt attention (left), the user's gaze direction indicates the attention of the users. Therefore using eye trackers help to tracks overt attentions. However, in the covert attention (right), the user gaze direction is on the monitor, but the attention is allocated to the time.

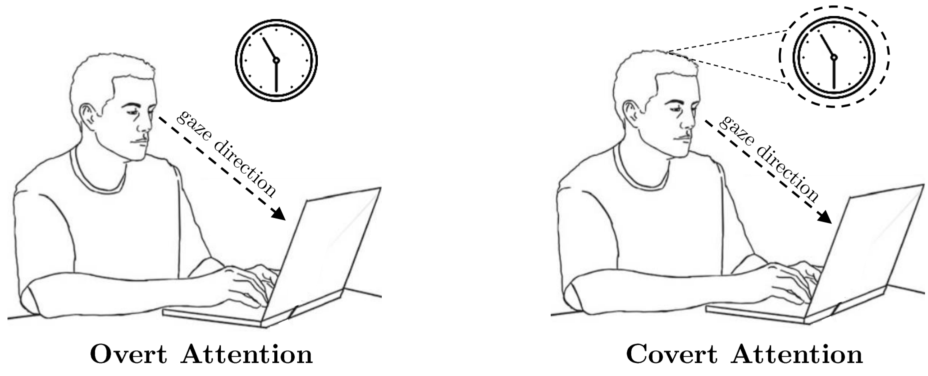


Figure 2.3.: An example of overt and covert attention.

The attention term used in this study is considered as goal-directed attention and the overt attention tracked by users' eye movement data. To control stimulus-driven attention, I designed a specific dashboard layout, which is discussed separately for each study.

2.2.2. Working Memory

Following the APA dictionary of psychology [3], memory is *"the ability to retain information or representation of past experiences, based on the mental processes of learning or encoding, retention across some interval of time, and retrieval or reactivation of the memory"*. Humans use their memory daily to process information around them, which has many different forms, e.g., images, sounds, or meaning. To explain how the memory works, Atkinson and Shiffrin (1968) proposed the *"Multi-Store Model of Memory"*. Based on this model, the memory comprises three stores: a sensory memory, short-term memory, and long-term memory. Sensory memory stores the raw information that the brain receives from the five senses. After paying attention to such information, the information is encoded, and then the short-term memory receives the input from the sensory memory. Later, rehearsing of information enables the transfer of information to long-term memory and keeps it for a longer time. As Figure 2.4 shows, based on this model, users process information trough three different memory types in a linear way and attention is the key element to transfer information around the user to the short-term memory.

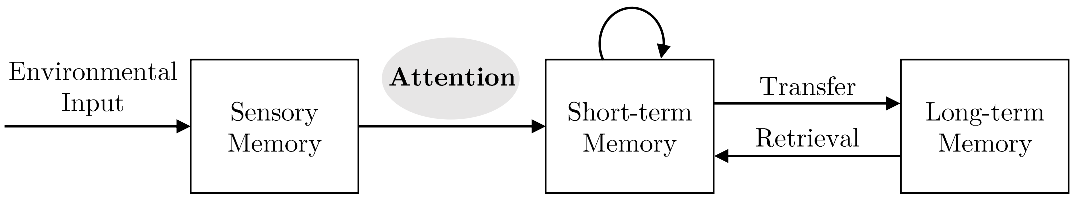


Figure 2.4.: Multi-store model proposed by Atkinson and Shiffrin (1968).

[3]https://dictionary.apa.org/memory

Later, researchers found that this model is oversimplified, and the short-term memory is a more complicated phenomenon that what is explained in the multi-store model of memory. Baddeley and Hitch (1974) have proposed an alternative model called *"Baddeley's Model of Working Memory"* and argued that the short-term memory is more than just a store. They argued that the short-term memory includes both store and processing information capability simultaneously. Therefore, they replaced the concept of short-term memory, which can only store information with *"Working Memory"* that can both store and process information. They argued that working memory could further be divided into three component, including the phonological loop, visuospatial sketchpad, and central executive Baddeley and Hitch (1974). The first two components describe in what kind of form, the working memory is storing information. The phonological loop is responsible for storing and processing verbal information; the visuospatial sketchpad focuses on storing and processing visual inputs such as spatial location, shape, size, and color. The third component is the central executive component, which is the most complicated part. This component describes the use of brain resources with working memory. It is also responsible for monitoring and coordinating the operation of other components and related them to long-term memory. Later, Baddeley (2000) added the fourth component as the episodic buffer that focuses on the relationship between short-term and long-term memory, synthesizing information across modalities, and interacting with semantic knowledge. Figure 2.5 shows the four components of working memory, and the relationship between as integrated by Baddeley (2012).

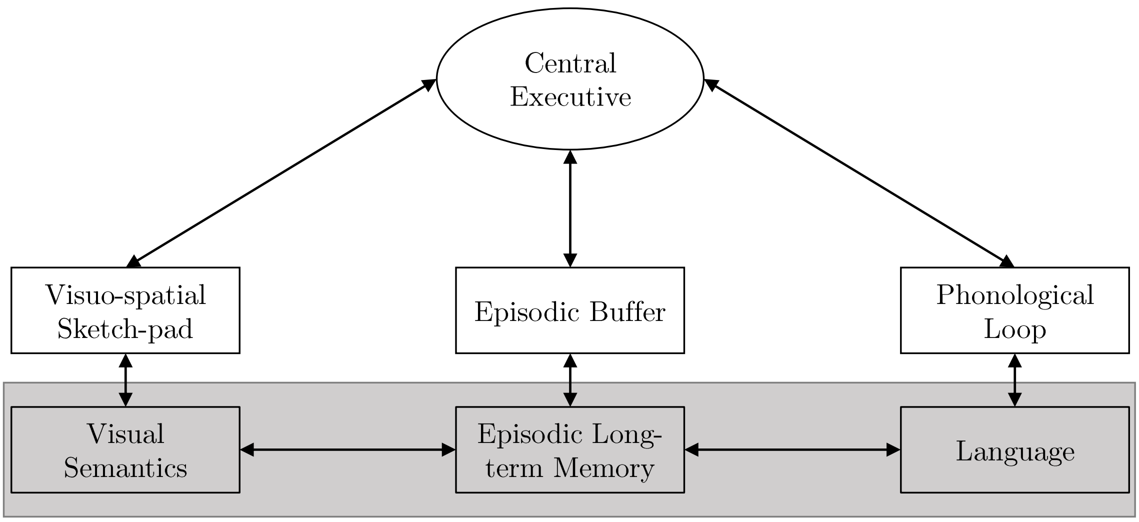


Figure 2.5.: Updated version of Baddeley's model of working memory by Baddeley (2000).

Working memory has an impact on building contemporary global models of cognition and is involved in many complex cognitive behaviors, such as comprehension, learning, reasoning, and problem-solving (Baddeley, 1992; Engle, 2002). Baddeley (2012) reviewed the working memory research and mentioned that the term *"working memory"* and *"short-term memory"* are still on occasion used interchangeably. However, he uses short-term memory to refer to the simple temporary storage of information and uses the working memory term to consider a combination of storage and manipulation. In this thesis, I follow the distinction between short-term memory and working memory and the term working memory used in the following studies refers to more than just a temporary store and consider as an element that influences users ability to control attentional resources.

Furthermore, working memory has a limited capacity (Cowan, 2010; Miller, 1956). Miller (1956) argued that this capacity could be increased by a process known as *"chunking"* which is grouping pieces of related information. A limiting number of items that can be recalled is known as memory span. It is known as one important individual difference (Baddeley, 1992). The memory span of individuals for the different forms of information (visual, verbal, digit, etc.) is not similar and there are different psychological tests to extract the users' memory span based on the information type (Conway et al., 2005; Wilhelm et al., 2013). This individual difference has an impact on real-world cognitive tasks (Engle, 2002) and general intelligence (Conway et al., 2003). Furthermore, several studies, such as Engle et al. (1999), Kane et al. (2001), and Kane and Engle (2003), have investigated the role of WMC and attention control. The results show that users with high and low capacity have different abilities to control their attentional resources, impacting their task performance.

2.2.3. Human Information Processing

The humans' mind is a information processing system (Card, 1983). HIP theory describes how individuals encode information, capture it in their memory, and retrieve it when needed. Researchers have considered the multi-store model of memory by Atkinson and Shiffrin (1968) and its linear process of information as HIP. However, this model does not fully consider the role of attention and working memory while processing information and has focused on three types of memory and their connections. Therefore, I use the adapted version of HIP stages by Wickens et al. (2016) in this thesis, which describes the relationships between different components of information processing in more details. Figure 2.6 depicts the stages of information processing. This framework includes four primary components: attention, memory, perception, response selection, and execution. I explain each of them in the following by considering the processing visualized information in the form of information dashboard.

"Attention" is the first component and has connections with all the other components. It is considered as a limited resource and the detailed description of it is discussed in Section 2.2.1. Healey and Enns (2012) explain that allocating limited attentional resources while processing visualized information contains two different steps. First, pre-attentive processing that includes methods for drawing the user's stimulus-driven attention. In this step, users encode a stimulus for a short time based on the elements that attract users' attention and perceive the information through their sense organ (e.g., eye, ear, etc.). Later, the central processing starts as the post-attentive processing that focuses on goal-directed attention and processing the perceived information in detail. Furthermore, the interaction between users and information visualization is through their visual systems. Therefore, overt attentional resources are used in this thesis as the attention component. Haroz and Whitney (2012) have investigated the role of limited attentional resources influence while processing information visualization processing. As a result, they found that this limited resource strongly changes the effectiveness of information visualizations, particularly the ability to detect unexpected information. Therefore, I assume that allocate attention to information dashboards properly influences the effectiveness of them as well.

"Memory" is the second component and different types of it are discussed in detail in Section 2.2.2. This framework comprises three types of memory and presents their relationship similar to what is introduced by Atkinson and Shiffrin (1968) as the multi-store model of memory and further updated by Baddeley and Hitch (1974) with the working memory concept. Based on that, first, the sensory memory stores the raw information that the brain receives from the sense organ (e.g., color, shape, location, etc. of the stimuli) and keeps it for few seconds. Second, working memory stores information temporarily and executes cognitive functions. Users select stimuli from the dashboard and precept it by allocating attention to the sensory memory's collected information besides previous experience collected in the long-term memory (experience level). Later the precept information is transferred to the working memory, which plays an important role in complex cognitive behaviors, such as comprehension, reasoning, and problem-solving (Engle, 2002). However, as discussed in Section 2.2.2, WMC is a limited resource. Researchers also have defined it as one important individual characteristic while working with visualized information (Borkin et al., 2016,1; Healey and Enns, 2012; Toker et al., 2013). Third, the long-term memory that stores the information for a long time. Rehearsing the information from working memory enables that information transfers to long-term memory.

"Perception" is the third component that helps raw data from the environment be interpreted and decoded. Wickens et al. (2016) have emphasized that perception and sensation are different since perception involves determining the *meaning* of sensory information. Perception of visualized information support users in making decisions in later steps (Ware, 2012). Ward et al. (2010) have distinguished the perception of visualized information as processes of recognizing (being aware of), organizing (gathering and storing), and interpreting (binding to knowledge). Therefore, the perception of information presented on information dashboards is considered as determining the meaning of the presented data.

"Response Selection and Execution" is the fourth component focusing on when users want to trigger an action based on the processed information. The selection of responses and the execution of the action are two separate stages. In the selection stage, the user makes a decision among several options. The process of making a decision can vary depending on the task. Also, the user may make a decision immediately, or store information while a decision is formulated. Later in some cases, this response is executed in a manner that requires muscle co-ordination for moving the body or execute some actions on the User Interface (UI). Hence this execution process may change the environment or UI layout (e.g., filtering a chart based on last year's sales amount); it creates new information that needs to be sensed. This loop is shown as the **"Feedback"** element in the framework that captures that the goal has been achieved.

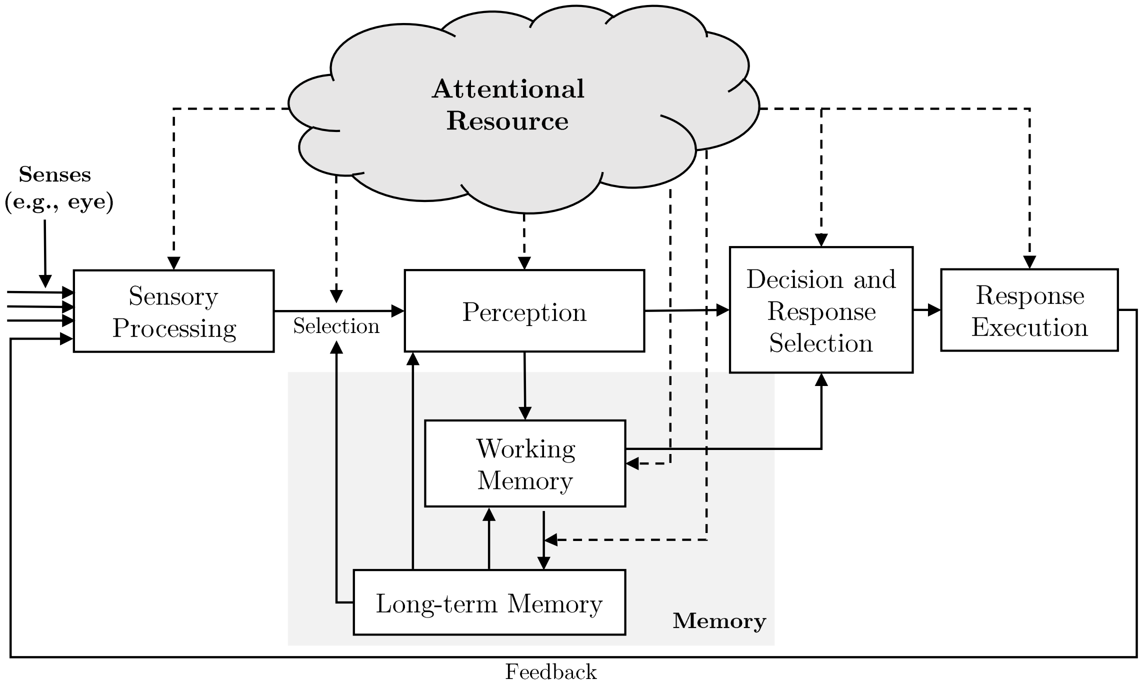


Figure 2.6.: A model of HIP stages adapted from Wickens et al. (2016).

2.3. Related Work

2.3.1. Eye Tracking Technology

Human's eyes are considered as a powerful sensory organ that they use them while processing information. With existing muscles around the eyes, humans can move them to place the information that interests them on the fovea. Therefore, eyes support perceiving visual impressions of what happens around us. The human's eye movement data demonstrates cognitive processes and gives a hint about what they are thinking or what may be their intention (Hayhoe and Ballard, 2005; Liversedge and Findlay, 2000; Rayner, 1998). This motivates the usage of it for in IS field (Dimoka et al., 2012) and it is also known as the dominant tool for IS studies that integrated neuroscience tools (Riedl et al., 2017).

Eye tracking technologies developed over a century ago to investigate human visual perception (Rayner, 1998). During the last century, it improved from both discovery eye movement facts and the relationship to cognitive behavior besides the recording systems. Using eye tracking technology and collecting eye movement data can describe the overt attention (Kowler, 2011). Yarbus (1967) has investigated the relationship between users' eye movement data and their intentions. Based on that, the participants received a photo and had to inspect it for different tasks. The results show that eye movements' pattern is different based on the viewer's intent or the task assigned. Therefore, knowing where an individual is looking at and tracking their eye movements patterns provides valuable information about user intentions. This capability have motivated researchers in different fields to use eye tracking technology, including neuroscience, psychology, ergonomics, advertising, and design (Richardson and Spivey, 2004). Eye trackers are not only proper for finding users' conscious behavior (e.g., visual attention, cognitive processes and intentions (Kowler, 2011; Majaranta and Bulling, 2014; Raptis et al., 2016)), they are also acknowledged as a promising approach to obtain insights on unconscious behavior (e.g., boredom (Kim et al., 2018), mind wandering (Bixler and D'Mello, 2016)).

Different types of eye trackers exist in the market and have been used by researchers in the last years (Duchowski, 2017; Holmqvist et al., 2011). Modern eye trackers use mainly near-infrared technology as well as high-resolution cameras to track the gaze direction. They are principally categorized into either desktop-mounted eye trackers (also called remote devices or screen-based) or head-mounted eye trackers (also called mobile eye trackers, eye tracking glasses, etc.). The desktop-mounted eye trackers are used to trace any desktop-based stimulus, while the head-mounted eye trackers are proper for real-life activities. Desktop-mounted eye trackers are more comfortable, easy to use, and faster to setup (Morimoto and Mimica, 2005) but limited the technology to the time that users are working with monitors. But using head-mounted devices is appropriate for everyday usage (Bulling and Gellersen, 2010). Head-mounted devices are very accurate and stable; however, desktop-mounted eye trackers may lose their accuracy when users change their distance from the eye tracker. Eye trackers in both categories tend to be expensive. Therefore, some studies have attempted to employ low-cost or open-source alternatives during the last years, e.g., using webcams (Burton et al., 2014; Zugal and Pinggera, 2014). However, in such eye trackers, high accuracy and compatible analytical software are critical for becoming successful. Besides these types, by enabling eye trackers on Virtual Reality (VR) and Augmented Reality (AR) headsets, the system can record the user's visual behavior for usability purposes or design new interactive features in the virtual environment by integrating the user's eyes.

The usage of eye tracking technology increased during the last years since there are cheaper, faster, more accurate, and easier to use eye trackers in the market (Duchowski, 2017). In this thesis, I used the Tobii 4C eye tracker [4] for both designing attentive information dashboards with VAF and conducting eye tracking studies to analysis users visual behavior. As shown in Figure 2.7, this apparatus is a desktop-mounted eye tracker with the size of 17 x 15 x 335 mm (0.66 x 0.6 x 13.1 in) and the sampling rate of 90 Hz. For applying this apparatus for research purposes, I used the relevant license to record and analyze the eye movement data.

Also, different metrics are used to classify the collected data through eye trackers. Holmqvist et al. (2011) and Duchowski (2017) have provided a long list of eye tracking data used in previous eye tracking studies. There are two fundamental concepts regarding eye movement data. First is the fixation, which is known as maintaining the visual gaze on a single location. During fixation, the gaze stops relatively on one object to process it. For that, a fixation needs to be around 200-300 milliseconds long. *"Approximately 90% of viewing time is spent in fixations"* (Duchowski, 2017, p.15). The second concept is *"Saccades"* which are known as the fast eye movements in between two fixations. Saccades can explain a voluntary change in the focus of attention (Duchowski, 2017). Besides eye movements, the pupils can give insights about mental processes. The pupil diameter is used to measure the

[4] https://gaming.tobii.com/tobii-eye-tracker-4c/

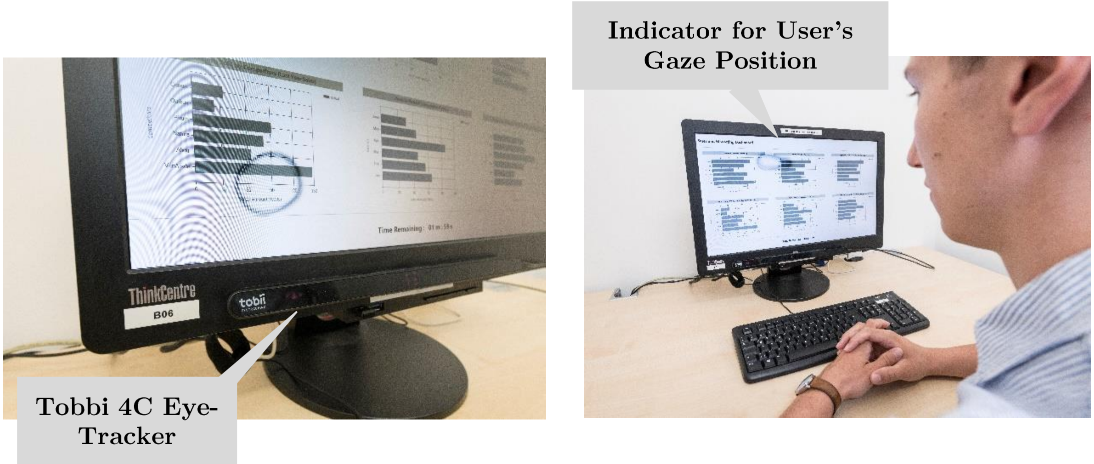


Figure 2.7.: Tobii 4C eye tracker with the sampling rate of 90 Hz.

user's cognitive load, which is higher for a bigger dilation (Holmqvist et al., 2011, p.393). Pupil dilation can also be a measurement to indicate a user's interest; a larger diameter leads to higher interest. Furthermore, there are several techniques to visualize the eye tracking collected data to understand users' visual behavior. Blascheck et al. (2014) have presented an overview of visualization techniques for eye tracking data and have described their functionality in nine categories.

There are several eye tracking applications that process and integrate eye tracking data. In general, Duchowski (2002) has broadly categorized eye tracking applications into the classes of diagnostic and interactive. In the diagnostic applications, researchers use the eye tracker to provide quantitative evidence of the user's overt attentional processes. Diagnostic eye tracking applications collect user's eye movement data while doing a task, and later, researchers use off-line records for the evaluation. The second category is interactive eye tracking applications that interact with the user based on observed eye movement data. In this case, the system uses the user's eye movement data in real-time and enable eye-based interactions. Furthermore, Majaranta and Bulling (2014) have categorized gaze interaction applications into four categories. Figure 2.8 depicts these applications based on the continuum from real-time to off-line recordings of eye movement data. The first category is **"Explicit Eye Input"** that refers to the applications which use gaze-based command and control. Different input possibilities have been tested and often compared to input through mouse and keyboard (Jacob and Karn, 2003) such as gaze typing (Majaranta and Räihä, 2002), gaze input (Hutchinson et al., 1989) and interaction with mobile devices (Drewes et al., 2007; Dybdal et al., 2012). Zhai (2003) presented an overview about using eye movements as an input interaction. Although using eyes as input is fast and useful in different cases, humans might look at a specific element for processing information and not intended to give a command. Jacob (1991) has introduced this problem as *"Midas Touch"* effect. The solution for that can be using other input modalities, such as gesture or voice, besides eye input. The second category is **"Attentive User Interface"** in which the users' eye movement data is used subtly in the background to provide attention support features. Eye trackers have the capability to collect eye movement data in real-time and use it for designing AUIs (Bulling, 2016; Henderson et al., 2013; Majaranta and Bulling, 2014; Roda and Thomas, 2006; Vertegaal, 2003). In this thesis, I focus on this type of eye tracking application and present a more detailed description of that in the next session. The third category is **"Gaze-based User Modeling"** systems in which tracking users' eye movement data provides a way for understanding the users' behavior, cognitive process, or intention. Researchers used eye trackers to identify user's confidence (Smith et al., 2018), intention (Doshi and Trivedi, 2009), workload (Bailey and Iqbal, 2008), engagement (Ishii et al., 2013), task (Steichen et al., 2014), learning curve (Lallé et al., 2015), personality traits (Hoppe et al., 2018), etc. The fourth category is **"Diagnostic Applications"** that works with passive eye monitoring and has a similar goal of diagnostic applications introduced by Duchowski (2002).

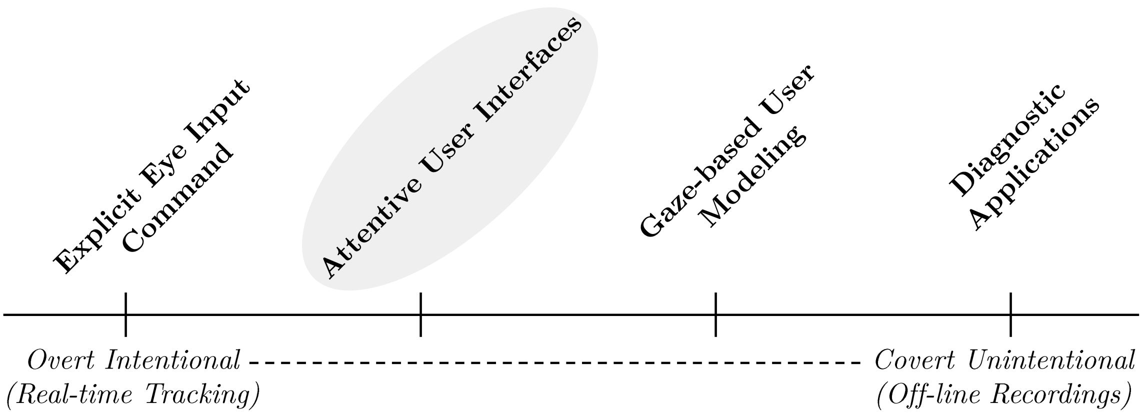


Figure 2.8.: Categories of eye tracking applications by Majaranta and Bulling (2014).

2.3.2. Attentive User Interfaces

The research on systems sensitive to the users' attention arose from the idea that a massive amount of the information surrounds the users in these years while their attention is a limited resource (Anderson et al., 2018; Bulling, 2016). Lack of proper attention allocation can cause different errors, which are known as attentional breakdowns (Roda, 2011). For example, the failure to notice a fully visible but unexpected content in UIs can be explained by the phenomenon named inattentional blindness (Mack and Rock, 1998), or the inability to detect changes because of lack of proper attention allocation as change blindness (Simons and Rensink, 2005). The developed conceptual framework as the result of Study I shows that attention support systems aim to assist users in overcoming such attentional breakdowns by adapting the system without involving users (e.g., (Buscher et al., 2012)) or providing feedback to increase their awareness (e.g., (D'Angelo and Gergle, 2018)). To assist in attention management, systems use user attention indicators such as user presence, proximity, orientation, speech activity, or gaze (Vertegaal, 2003) as an input and provide attention support feature.

This type of system is known as AUI and Vertegaal (2003, p.32) has described it as *"Computing interfaces that are sensitive to the user's attention"*. Later, Roda and Thomas

(2006, p.577) have introduced attention-aware systems as another type of attention support system as *"systems capable of supporting human attentional processes"*. They argued that such a system is helpful in different domains, mainly where:

> "...(1) attentional switches are very often solicited, or (2) where the users' lack of experience with the environment makes it harder for them to select the appropriate attentional focus, or (3) where an inappropriate selection of attentional focus may cause serious damage to the system, its users, or third parties, or (4) where the very reason for the system to exist is to attract the user attention".

Also recently, Bulling (2016) has suggested using real-time eye movement data beyond specific situations and proposed pervasive AUI. This type of system aims to continuously track the user's eyes and manage their attention for daily life activities. Such systems can simultaneously optimize for both information throughput and subtlety. Future AUI will support users' attention management process in daily life (Bulling, 2016).

In this thesis, I focus on integrating attention support systems while users work with IS applications at workplaces. Therefore, the definitions of AUI and attention-aware systems fit my intention. As both AUI and the attention-aware system have close meaning (Roda and Thomas, 2006) and have the same goal, I choose AUI as the key terminology in my thesis and refers to attentive information dashboard as a type of AUI.

Furthermore, users' eye movements can be used as input for designing intelligent UIs (Henderson et al., 2013), and their usage has grown during the last years (Nakano et al., 2016). This data is known as one of the popular data sources for designing AUIs (Bulling, 2016; Majaranta and Bulling, 2014). Such AUIs are used in different fields so far. Examples of AUIs are: reading assistant by attentive documents (Buscher et al., 2012), attentive information systems (Maglio et al., 2000), attentive recommender systems (Xu et al., 2008a), attentive tutoring systems (D'Mello et al., 2012), support resuming interrupted tasks (Kern et al., 2010; Mariakakis et al., 2015), attentive conversational agents (Ishii et al., 2013). The results from a SLR study as Study I in this thesis provides an overview of existing systems.

For IS application, Maglio et al. (2000) have suggested in integrating users' eye movement data for designing attentive IS. This type of IS application should gather evidence about users' behavior from multiple sources, model the user, and present extra information to support their task. Furthermore, they suggested using users' gaze information as one source of information for attentive IS. Based on the developed conceptual framework in Chapter 3, this type of support is considered a system adaptation focus. However, the best of my knowledge there is no attentive IS focusing on user adaptation and increasing users' self-awareness.

2.3.3. Business Intelligence and Analytics Systems

With the use of advanced information technologies, companies have the opportunity to make informed decisions and take faster actions by using data resources (Phillips-Wren et al., 2015; Torres et al., 2018). The usage of Business Intelligence and Analytics (BI&A) systems has become more important for companies over the last years (Peters et al., 2016; Trieu, 2017).

BI&A systems have gone through its evolution during the past decades. It is not an entirely new phenomenon and can be traced back to the middle of the 20th century (Watson, 2009). In the 1960s, organizations used computers for transaction processing and scientific applications. The focus did not lie on decision support back then and later, the first system to support making decisions was developed to help managers achieve specific business goals. Over the years, various applications for this purpose have been developed and named differently, like Executive Information Systems (EIS), Management Information Systems (MIS), or Decision Support Systems (DSS). In the early 1990s, the term Business Intelligence (BI) was first introduced by Howard Dresner (Power, 2007), who has described it as *"an umbrella term for all decision support applications"* (Wixom et al., 2011, p.13). The popularization of the BI term in the 1990s was reinforced by the development of IT infrastructures like the internet and large database systems enabling data warehousing (Dinter et al., 2015). In the beginning, the focus of BI was mostly on technological aspects resulting from new developments in the application of analytic systems like Online Analytical Processing and Data Mining (Chaudhuri and Dayal, 1997; Fayyad et al., 1996). Later, other BI specific topics evolved like the integration of mass data with the help of extract, transform, and load processes, the design of different architectures of data warehouse systems, the modeling of the query-oriented data schema, as well as the pursuit of improvement and assurance of data quality (Wang and Strong, 1996). At the beginning of the 21st century, researchers and practitioners shifted their focus from the rather technical aspects to more strategic, organizational, and integrative dimensions of BI. Also, there was a change of focus within the technical aspects like the collection of web-based, unstructured content in social media, content and text analytics, etc. It offered new opportunities for businesses to analyze their customers' opinions, analyze mobile and sensor-based content, etc. More recently, with billions of people carrying smartphones and other GPS devices, location-aware analysis, and person-centered analysis emerge in the context of mobile BI and the internet of things as well (Chen et al., 2012).

Chen et al. (2012) have introduced the BI&A concept as the next version of BI. Whether they are called DSS, MIS, EIS, BI, or BI&A the purpose of all of these systems is the same, namely, to provide managers with information to support their decisions and the terms are often treated synonymous (Chen et al., 2012). Due to the opportunities that are collecting and analyzing data provides, the interest in BI&A is significant these days, and I consider BI&A following the definition have presented by Chen et al. (2012) as:

> "... the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions".

2.3.4. Information Dashboards

To support decision-makers, BI&A systems are generating insights by using analytical techniques and then envisioning them in the form of visualized information. The primary purpose of information visualization is to support users in perceiving patterns, which can be used to build appropriate explanatory models and support improving performance (Purchase et al., 2008). Also, information visualization ease in finding the relationships among data and provide a comprehensive overview of the data (Kelton et al., 2010).

Information dashboards are known as one of the most effective BI&A tools (Negash and Gray, 2008) that show the current status of metrics and key performance indicators of an entire company or sub-division (Pauwels et al., 2009). An information dashboard typically combines numbers, metrics, charts, graphs, etc. on one screen, and users need to explore them at the same time and find relationships between them before making decisions. The information dashboards can be customized for specific roles and show metrics that are optimized for a particular business task. Dashboards usually process data from different sources in real-time and include design features that support users to customize the layout based on their intention. The users of dashboards may have different purposes include consistency, monitoring, planning, and communication (Yigitbasioglu and Velcu, 2012). By using them, the user may search for information or scan the whole dashboard to understand the current business state (Vandenbosch and Huff, 1997). Few (2006, p.34) has defined information dashboards as:

> "... a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance".

Furthermore, Yigitbasioglu and Velcu (2012) have described an information dashboard for management purposes as:

> "collect, summarize, and present information from multiple sources such as legacy, enterprise resource planning, and BI software so that the user can see at once how various performance indicators [...] are performing".

The proper usage of information dashboards and matching it to the decision-makers' tasks are known to affect the success of such systems (Schwarz et al., 2014). Also, having interactive information dashboards are considered as one of the critical elements for BI&A systems (Cindi et al., 2019; Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). Information dashboards support decision-makers in their thinking process (Bačić and Fadlalla, 2016). Therefore, they should be designed to help decision-makers maintain their cognitive tasks in convenient ways. To reach that goal, they need to be evaluated according to their design features and the way the users interact with them for making decisions. They can also be equipped for new features and support users in conducting their cognitive (Niu et al., 2013; Yigitbasioglu and Velcu, 2012).

The interaction between decision-makers and information dashboards is mainly focused on investigating the information visualization (Tegarden, 1999). In existing dashboard studies, researchers have used eye trackers to evaluate the design features (e.g., presentation formats, colors, size, etc.) by analyzing off-line records of eye movement data (Bera, 2014,1; Burch et al., 2011). Besides that, they investigated the visual analytics strategies of decision-makers to find the relationship between the accuracy, speed, and consistency of decisions (Cöltekin et al., 2010; Vila and Gomez, 2016), user's cognitive effort while working with visualized information (Fehrenbacher and Djamasbi, 2017; Smerecnik et al., 2010), and their situation awareness (Nadj et al., 2020). Researchers also used eye movement data to examine the relationship between user characteristics and visualized information such as perceptual speed, visual and verbal working memory (Okan et al., 2016; Toker et al., 2013). The main focus is on integrating this technology for evaluation purposes (Kurzhals et al., 2016). Silva et al. (2019) have argued that only a few studies investigated using eye movement data in real-time and they have focused on system adaptation (e.g., (Okoe et al., 2014; Shao et al., 2017; Silva et al., 2018)) rather than increasing users awareness. The results from the SLR study in Chapter 3 shows that no study has used real-time eye movement data for designing attentive information dashboards that provide attention support features.

3. State-Of-the-Art and Conceptual Framework [1]

3.1. Study I: Overview

Researchers have studied the collection and usage of user's gaze data in two major modes, the off-line and real-time mode, (Majaranta and Bulling, 2014). In the off-line mode, collected gaze data is analyzed after a task has been performed. Typically, the *off-line* mode is used for diagnostic purposes and has been the most well-known usage scenario of eye trackers. Using eye trackers for diagnostic purposes is popular among researchers since it provides objective data about users, which is enhancing subjective self-reported data, e.g., collected using surveys. Researchers have intensively used eye trackers for the off-line mode in various fields. They have integrated highly accurate and expensive eye trackers to explore user visual behavior while interacting in digital or physical environments and model user cognitive states while conducting tasks (Hayhoe and Ballard, 2005; Kowler, 2011; Liversedge and Findlay, 2000; Orquin and Mueller Loose, 2013; Rayner, 1998). With the further advancement of eye tracking technology during the last years, researchers have increasingly leveraged the possibility of collecting and processing user eye movement data in *real-time*. With the real-time mode researchers can involve the users' eye movement data in an interactive system and create gaze-responsive applications (Duchowski, 2002). These applications offer new ways of interacting with systems, including two main paradigms: 1) using eyes as an input device for interactive systems or 2) collecting and analyzing user eye movement data in real-time to design Interactive Intelligent Systems (IIS). Integrating user gaze data as input for designing IIS has grown during the last years (Nakano et al., 2016). Besides attention detection as the primary purpose of tracking user eye movement data (Carrasco, 2011), the usage of it is suggested to extend user context with cognitive dimensions (Bulling and Gellersen, 2010) including user's confidence (Smith et al., 2018), intention (Doshi and Trivedi, 2009), workload (Bailey and Iqbal, 2008), engagement (Ishii et al., 2013), task (Steichen et al., 2014), learning curve (Lallé et al., 2015), personality traits (Hoppe et al., 2018). In this state-of-the-art study, I consider systems that process eye movement data in real-time to design IIS as eye-based IIS.

The research gaps regarding this study are already discussed in Section 1.2. In this study, I summarize existing knowledge about eye-based IIS by conducting a SLR study and integrating the results in a conceptual framework. Furthermore, I provide a list of future research directions for eye-based IIS. Best of my knowledge, such review does not exist, and current literature reviews focus on summarizing the usage of eye trackers in specific fields rather than integration for designing IIS. Therefore, I focus on closing this gap by answering the first RQ of this thesis as following:

> ***RQ1:*** *What is the state-of-the-art and potential future research directions for designing eye-based IIS?*

[1] This Chapter is based on the following working paper: Toreini and Maedche (2020)

This RQ is the step before conducting the DSR project in this thesis and has the aim to provide an overview of existing knowledge in eye-based IIS to support designing attentive information dashboards in the next steps. To answer this RQ, I first introduce the foundations of eye-based IIS in Section 3.2 with an integrated conceptual framework, including key dimensions for designing such systems. Subsequently, I introduce the methodology used to conduct SLR study in Section 3.3. Next, in Section 3.4, I present the findings for each dimension of the developed conceptual framework in detail. Last, Section 3.5 contains discussion and suggestions for future research direction in this field before concluding this study in Section 3.6.

3.2. Conceptual Foundations

In this section, I first introduce the concept of eye-based IIS and define it. Subsequently, I describe the integrated conceptual framework which is derived in this study and is used to report the state-of-the-art review and future research directions.

3.2.1. Eye-based Interactive Intelligent Systems

Jameson and Riedl (2011) introduces IIS as intelligent systems that people interact with, and they emphasize the interplay of intelligent technology with advanced interactions of users a system. By applying intelligent technology, a system embodies capabilities that have traditionally been associated with humans. An example of that is the ability to perceive information, learn, reason and plan. Complementary, the focus on advancing interaction design for intelligent systems emphasizes the need to understand users better and support them when interacting with systems. Thus, IIS combines intelligent algorithms and advanced interactions to promote the interaction between users and the system.

The usage of user gaze data leveraging eye tracking technology as input for designing intelligent systems has grown during the last years (Henderson et al., 2013). The primary usage of the eye movement data in real-time is to track user's attention (Carrasco, 2011). Based on that, Vertegaal (2003) introduces the concept of Attentive User Interface (AUI) as computer interfaces that are sensitive to the user attention mainly by tracking user eyes and model the user's visual behavior. Since an AUI knows the status of user attention, it can raise the interaction between users and the system accordingly by either providing attention support features or adapt the system best on user status. Nguyen et al. (2018) provided a comprehensive review of attentive systems that use saliency cues. Later, Roda and Thomas (2006) introduced attention-aware systems, which has a similar goal to AUIs and are capable of supporting human attentional processes. Similar to AUIs, eye trackers are proposed as the primary device for designing such a system as well. Recently Bulling (2016) has suggested pervasive AUIs and usage of real-time eye movement data constantly. This type of system aims to track the user's eyes continuously and manage their attention for daily life activities. Such systems can simultaneously optimize for both information throughput and subtlety. Attention status of the users is the primary usage of real-time eye movement data and designing AUIs, attention-aware systems or pervasive AUIs are suggested based on that. However, these are not the only use cases for designing intelligent

UIs based on real-time eye-movement data. Analyzing eye movements can be used to derive other cognitive dimensions beyond attention and design cognition-aware interfaces (Bulling and Gellersen, 2010; Bulling et al., 2011). Eye trackers are also effective to understand user confidence (Smith et al., 2018), intention (Doshi and Trivedi, 2009), workload (Bailey and Iqbal, 2008), engagement (Ishii et al., 2013), task (Steichen et al., 2014), learning curve (Lallé et al., 2015), personality traits (Hoppe et al., 2018). The systems that used such information as input are called in different ways such as gaze-aware (Tremblay et al., 2018), gaze-reactive (D'Mello et al., 2012), gaze-contingent display (Duchowski et al., 2004) and gaze-directed display (Toet, 2006). A common characteristic of all eye-based systems is that eye tracking technology is the core device for collecting user gaze data. Later, the collected data is used to model user states and on this basis to design advanced interactions for its users. Therefore, I name IIS which leverages eye trackers as eye-based IIS. I assume that this class of systems does not only focus on attention but also covers other user states. Specifically, I define eye-based IIS as follows:

> "Eye-based interactive intelligent systems are intelligent systems that use eye tracking technology to collect user gaze data to model user states for designing advanced interactions between users and the system".

3.2.2. Integrated Conceptual Framework

I propose a conceptual framework for research on eye-based IIS after checking papers collected in this study, as depicted in Figure 3.1. In this framework, I distinguish three high-level categories in framework 1) influencing factors, 2) eye-based IIS properties, and 3) outcomes. Each category includes several specific elements. In the following sections, I introduce the conceptual foundations of each category, as well as their dimensions in detail. The proposed framework provides a foundation for capturing the current state of research and future research directions in eye-based IIS.

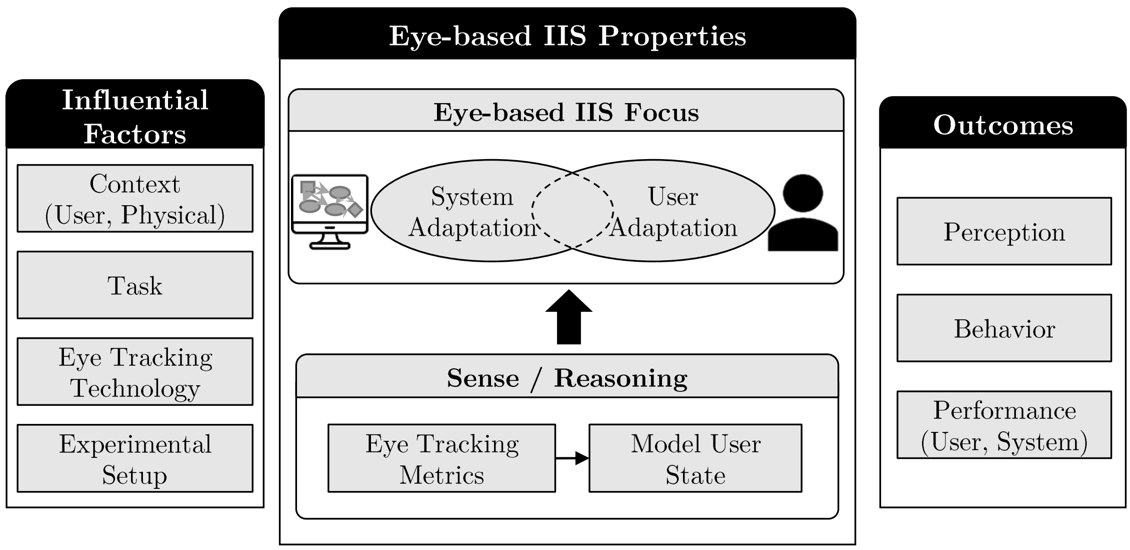


Figure 3.1.: Integrated conceptual framework for eye-based IIS.

Influencing Factors

The influencing factor category focuses on elements that impact the design of the eye-based IIS and its outcomes. Besides that, I concentrate on eye tracking technology as there are different types to be used for designing eye-based IIS. I also investigate how the developed systems are evaluated in which conditions.

As the first dimension in this category I consider ***Context***. The term context has been used in many ways in different research fields. Chen and Kotz (2000) have defined it as *"the set of environmental states and settings that either determines an application's behavior or in which an application event occurs and is interesting to the user"*. Schilit et al. (1994) have named these environmental states as physical context and added user conditions, including the user profile, social situation, location, etc. as another aspect of the designing context-aware systems. For designing eye-based IIS, I consider both the user and physical contexts and integrate it into the framework.

Beside context, I consider ***Task*** as the second dimension in this category. Context and task are known as two dimensions that guide the design of any interactive system (Benyon, 2013). Previous eye tracking studies have shown that the given task affects user eye movements patterns (Yarbus, 1967). Therefore I added task as another influential factor while the primary goal of eye-based IIS is to support users in increasing their task performance.

The third dimension in this category is the ***Eye Tracking Technology***. Different types of eye trackers exist in the market and have been used by researchers in the last years. Researchers in the field of eye-based IIS need to investigate which eye tracker fits their use case by considering different aspects such as usability, accuracy, and price. Modern eye trackers use mainly near-infrared technology as well as a high-resolution camera to track the gaze direction. Next to the camera emits infrared light, which produces a reflection on the cornea of the eye that its position changes depending on where the user looks (Morimoto and Mimica, 2005). Therefore, the point of gaze can be calculated by measuring the changing distance between the pupil and the cornea reflection (Majaranta and Bulling, 2014). Independent from the technical aspects to record the gaze position, eye trackers are principally categorized into either desktop-mounted eye trackers (also called remote devices or screen-based) or head-mounted eye trackers (also called mobile eye trackers, eye tracking glasses, etc.). The desktop-mounted eye trackers are used to trace any desktop-based stimulus, while the head-mounted eye trackers are proper for real-life activities or virtual environments. Details of eye tracking technology are discussed in Section 2.3 in Chapter 2.

Finally, I suggest to consider ***Experimental Setup*** as an important element. It is important to understand how researchers evaluated the designed eye-based IIS. Therefore I consider the experimental setup as an influencing factor. The experimental method includes laboratory or field study, type of study includes within, between, mixed, etc. The amount of participation in the collected studies can impact the conclusions about designed eye-based IIS.

Eye-based IIS Properties

The second category is focusing on the specific eye-based IIS properties, which are considered as the core of the framework. ***Sensing and Reasoning*** are key properties to design eye-based IIS. Later, these properties are used to design eye-based IIS, which can have two main ***Focuses***: making the system more intelligent and support system adaptation or increase user awareness and support user adaptation.

First, eye trackers are the main tool for sensing dimension in designing eye-based IIS. Different metrics are used to classify the collected data through eye trackers. I divided ***Eye Tracking Metrics*** into five high-level categories, including gaze-based, fixation-based, saccade-based, pupil-based, and others. Each of these categories comprises subcategories that I named as eye-gaze measures. Later, the collected data is analyzed to detect patterns in and draw conclusions on the user state. The reasoning dimension is about how the collected eye movement data is used for ***Modeling User State***. Collected eye movement data provides insights into the cognitive process and gives hints about the anticipated user behavior (Majaranta and Bulling, 2014). It is not only finding of their conscious behavior (e.g., relevance, interest, task, intend, etc.) of the users, but it is also acknowledged as a promising approach to obtain insights on unconscious behavior (e.g., boredom, mind wandering, etc.).

In general, IIS should include both human and artificial varieties of intelligence (Jameson and Riedl, 2011) while they aim to create novel interactions that suited to people's abilities. Eye-based IIS systems use the results from the sense and reasoning processes as an input to design such novel interactions. The designed novel interaction has two main focuses: 1) increasing the intelligence of the system by generating implicit feedback and focusing on system adaptation, 2) increasing user awareness by providing corrective feedback, and focusing on user adaptation. First, in the case of ***System Adaptation***, eye-based IIS focuses on intelligent technology and provides sense and reasoning results as input for designing better intelligent algorithms that later support users without involving them directly. In this case, the user is observed by the computer, and the system generates implicit feedback. Therefore, it adapts the interface to the user's needs and intentions while the user may not be aware of what is going on in the back end and the changes in the provided information. However, adapting the interfaces that users are working with can help them to use the system more efficiently. For example, Buscher et al. (2012) used the user's eye movement data as implicit feedback and designing attentive documents. Such documents are used for personalizing and improving the quality of web search. As another example, Rozado et al. (2015) integrated user gaze information as a source for user intention and use it to speed up web navigation and increase user comfort.

The second focus of eye-based IIS is on designing new interaction in which the system focuses on ***User Adaptation***. In this case, users are involved in advanced interactions and receive corrective feedback while conducting the task. Here, the corrective feedback role is to increase users' awareness and let them improve their information processing. To design corrective feedback, the computer adjusts the eye tracking data as gaze augmentation in real-time or present user eye movements history in forms of different visualization techniques such a heatmap, scanpath, last fixated point, etc. For example, D'Angelo and Gergle (2018) investigated how different forms of gaze visualization increase shared attention and therefore influence collaborative performance.

Outcomes

In the last category, I investigate the outcomes of the designed eye-based IIS through three dimensions. The first dimension focuses on ***User Perception*** in which I study how users clarified their experience while working with the eye-based IIS. User perception is usually measured by conducting a survey or interviews after experiencing a new innovative interaction. As the second dimension, I investigate how their ***Behavior*** is changed while working with eye-based IIS. Here, I focus on objective data collected during user interaction through different approaches, including data from user mouse and keyboards or by integrating other user tracking devices such as eye trackers. In the eye-based IIS studies, since the eye trackers are already used in the design process, I assume that researchers use the device for the evaluation sections as well and report users' visual behavior. As the third dimension, I consider the ***Performance*** measurements, which can have two perspectives. First, studies may review how using the eye-based IIS influences users' performance to conduct their tasks. This examination focuses more on the relationship between user performance and the provided innovative interaction by eye-based IIS. From the second perspective, studies may focus on the system's performance and consider the effects of the intelligent technology used in designing eye-based IIS.

3.3. Methodology

For executing the review, I followed the steps proposed by Kitchenham and Charters (2007). Based on that, the review process includes three main steps that include planning, conducting, and reporting. Each of these steps entails specific sub-activities. Figure 3.2 explains the three high levels and the subsections for each step and the activities. In the following, I describe each step for the plan and conduct steps in detail. Later I provide the findings in Section 3.4.

3.3.1. Planing the Review

In the planning, first, the need for the review must be identified. I already discussed the existing research gap and motivation for this review in Section 3.1. In the second part, I developed a conceptual framework in several iterations while exploring collected papers for this study. Later, this framework supports analyzing the collected papers in the review from different perspectives. The detail of this framework is already discussed in Section 3.2. Last, I developed a review protocol that covers the following aspects.

Sub-Research Questions: To follow a structured approach in selecting and later analyzing the collected papers, I articulated sub-research questions: (1) What are the boundary conditions of using eye trackers in designing innovative interactions? (2) How are innovative interactions conceptualized? (3) Which influencing factors are considered while

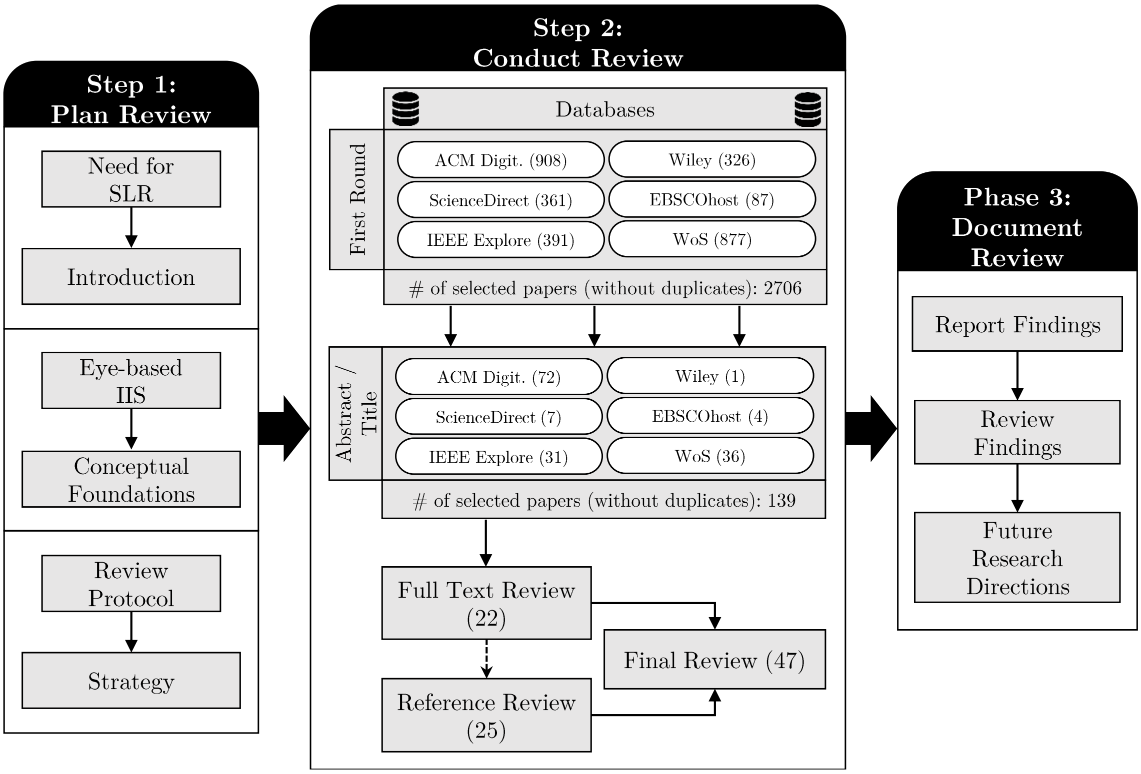


Figure 3.2.: Steps of the SLR study for designing eye-based IIS following Kitchenham and Charters (2007).

designing eye-based IIS? (4) Which eye-based IIS properties are used for designing eye-based IIS? (5) What are the outcomes of the eye-based IIS?

Search Strategy: Later, I developed a review protocol, which is supposed to be used as documentation for other researchers to re-run the review and get the same results. Once the aim of the study and the review protocol is defined, I generated a boolean string that includes keywords. These keywords are extracted after searching the ACM Intelligent User Interface conference and ACM Transaction of Interactive Intelligent Systems as two HCI outlets relevant to the eye-based IIS topic. I searched for *"eye OR gaze"* in these outlets, identified some relevant papers, and extracted a set of keywords from them. I categorized these keywords into four groups, as can be seen in Figure 3.3. The first two categories (eye and movement) are related to eye tracking technology and focus on finding the papers that include these devices. The other two categories cover the aspect focus on the domain of IIS. Later, I used the connecting operators in the way to search for each keyword-combination that represent both perspectives and support to extract eye-based IIS studies.

Subsequently, I selected six databases covering different research communities since eye tracking technologies have already been used by researchers in various fields: ACM Digital Library, ScienceDirect, IEEE Explore, Wiley, EBSCOhost, and WebOfScience. I used the search string to search on the title, abstract, and keywords section of the papers. I also chose a time limitation from beginning 2008 until the end of 2019, which covers the last 12 years for the initial search. In the backward search, I considered the same time limitation to provide a complete overview.

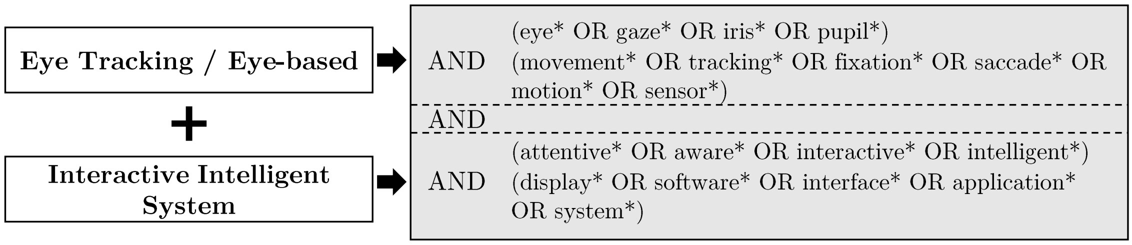


Figure 3.3.: Search string with four main categories to conduct the SLR study.

Study Selection Criteria: After collecting the papers, I applied several selection criteria only to include high-quality and relevant studies. First, I included only peer-reviewed publications. Second, I excluded research in progress papers. Third, I removed publications with less than five pages. Fourth, I excluded papers that used eye tracking only for diagnostic purposes. Fifth, I excluded papers that concentrated on increasing the quality of life for users with physical disabilities or cognitive impairments. Sixth, I excluded papers that apply eyes as an input device to directly control the system or use it in the multi-modal interaction set up. Seventh, I removed the papers that focus on modeling user behavior, cognitive processes, intentions, etc. without providing any innovative interactive system. With those selection criteria, I focused on the studies that use real-time eye movement data to model user state and later provide innovative interaction design as used in the definition for eye-based IIS in Section 3.2.

3.3.2. Conducting the Review

In this step, I first executed the search string in the six selected databases and found 2706 papers. Later I filtered relevant papers by reading their title and abstract and considering the pre-defined questions discussed in Section 3.3.1 and selection criteria in Section 3.3.1. The result of this step ends with 139 selected papers. Next, I read these papers in more detail and selected 22 of them that fit the definition of eye-based IIS and the goal of this review. Next, I conducted backward and forward search on these papers and added 25 more papers to the list. In the end, I selected 47 papers that are considered as eye-based IIS and published from the beginning of 2008 until the end of 2019. The list of selected papers can be seen in Appendix A.1.

A descriptive analysis of the final list of collected papers shows that the dominant research community for designing eye-based IIS is HCI by covering 81% of all papers. From the remaining 19% papers, 6% are in psychology and cognition community, 4% are published in the learning community, 4% in the visual computing community, 2% in multimedia, and 2% in system engineering. Looking in more detail into the HCI papers, 57% are published in top HCI outlets ranked by Google scholar [2] as well as ETRA conference as one of the important conferences for the eye tracking community. 26% of the papers are published

[2]https://scholar.google.es/citations?view_op=top_venues&hl=en&vq=eng_humancomputerinteraction

in CHI conferences and 31% in other outlets such as IEEE Transactions on Interactive Intelligent Systems, International Journal of Human-Computer Studies, IUI, UbiComp, ICMI, ETRA.

As depicted in Figure 3.4, one can clearly recognize an upward trend towards more research in the field of eye-based IIS nowadays. 60% of the papers were published in the past six years (2014-2019), while 40% of them are from 2008 to 2013. The reason for an increasing number of studies in this field during the last years may be the improvement of eye tracking technology as well as the availability of cheaper devices in the market. More details on these factors are discussed in the eye tracking technology dimension in Section 3.4.1.

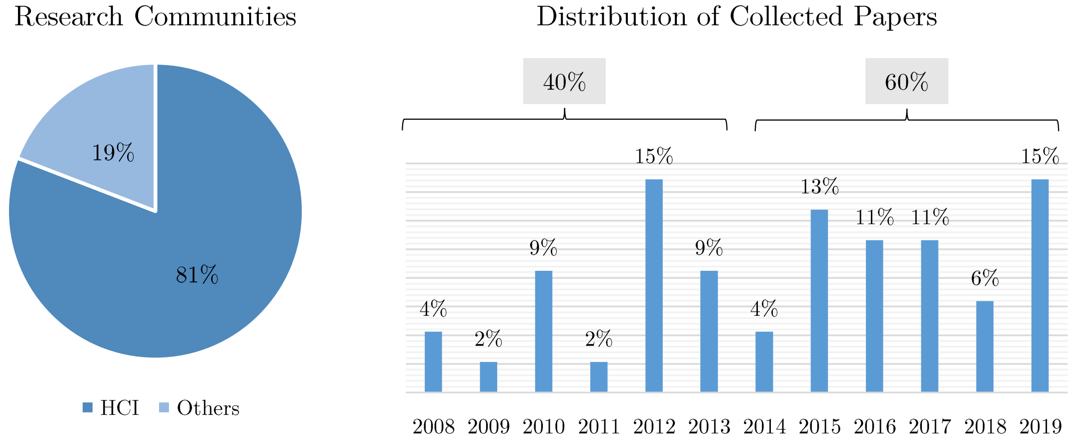


Figure 3.4.: Distribution of collected papers based on years and research fields.

3.4. Findings

I analyzed all 47 resulting papers using coding tables derived based on the developed integrated conceptual framework explained in 3.2. The detail of these coding tables can be seen in Appendix A.2. The results from analyzing the coding tables are used to report the state-of-the-art that I present in the following.

3.4.1. Influencing Factors

Context

Figure 3.5 summarizes the findings regarding the user context. Analyzing the collected studies show the individual interaction between users and the eye-based IIS is the dominant research focus regarding the user social context. 68% of the studies focused on the individual aspect, 30% focused on team-based and 2% on the collaboration between users and conversational agents. Furthermore, the participants' information reported in the conducted studies includes age (68%), gender (62%), experience level (45%), and vision status (19%) are the four metrics that are considered in the studies as the user profile. This distribution shows that the user age and gender are the two popular factors for profiling users. These four factors are the ones that researchers collected while evaluating

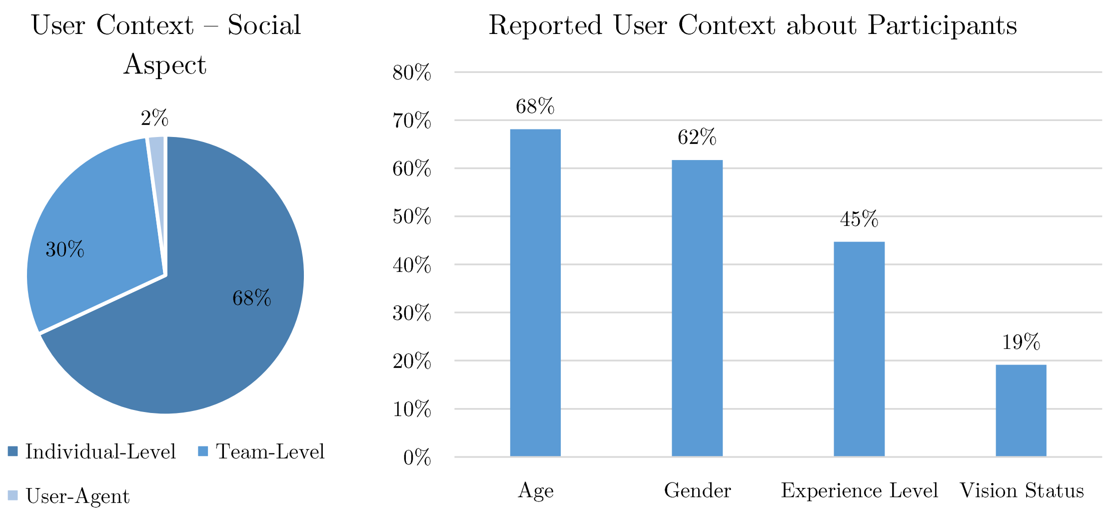


Figure 3.5.: Descriptive statistics: user context.

the designed eye-based IIS. Besides, user profiling can also be viewed as the user state collected by the eye trackers, which I discuss in Section 3.4.2.

Figure 3.6 presents the results regarding the physical context. First, I classified the physical context into digital and real-world environments. As can be seen, 96% of the collected studies focus on the eye-based IIS that works with digital environments, while only 4% consider designing such a system for real-world physical interactions. Furthermore, I analyzed the type of application that integrated the eye tracking system for designing eye-based IIS as another dimension for physical context. Figure 3.6 shows that collaboration tools are the most popular digital applications that are empowered with eye-based IIS (22%). Collaboration is the mutual work of two or more people either at the same time or consecutively. Lack of joint attention during communication can result in various problems. Therefore, eye-based IIS systems in this category typically focus on enhancing the collaboration between team members by providing a shared gaze feature. The team's participants focus on a common goal, such as writing a text, problem-solving, driving, learning, etc. that are discussed as the list of tasks in the next sections. Next, web-based applications (15%) are the popular physical context for designing eye-based IIS. In this case, the system integrated user eye movement data in real-time and extracted their state while exploring a website. As an example, such information is used to improve the performance of recommender systems in an online shop and provide more accurate items to the web users based on their interest collected through their eyes. The next popular digital application is exploration tools (13%), where users need to process huge amounts of information on the provided UI. In this case, eye-based IIS helps users manage information overload properly and prevent possible attentional breakdowns, such as missing important information or change blindness. For the next digital application, researchers focused on enhancing the effectiveness of training applications (13%) and support the user learning process by tracking their eye movement data in real-time. The collected information is used for adapting the learning content, inform the students about their learning process, inform the teacher about the status of their students, etc. Also, Reading tools (11%) that support the user in reading books, pdfs, texts, etc. as well as the driving simulators (11%), are popular among eye-based IIS researchers. Finally, gaming tools (7%), multi-display applications (5%), VR and AR platforms (2%), and cellphone apps (2%) are less interesting digital applications.

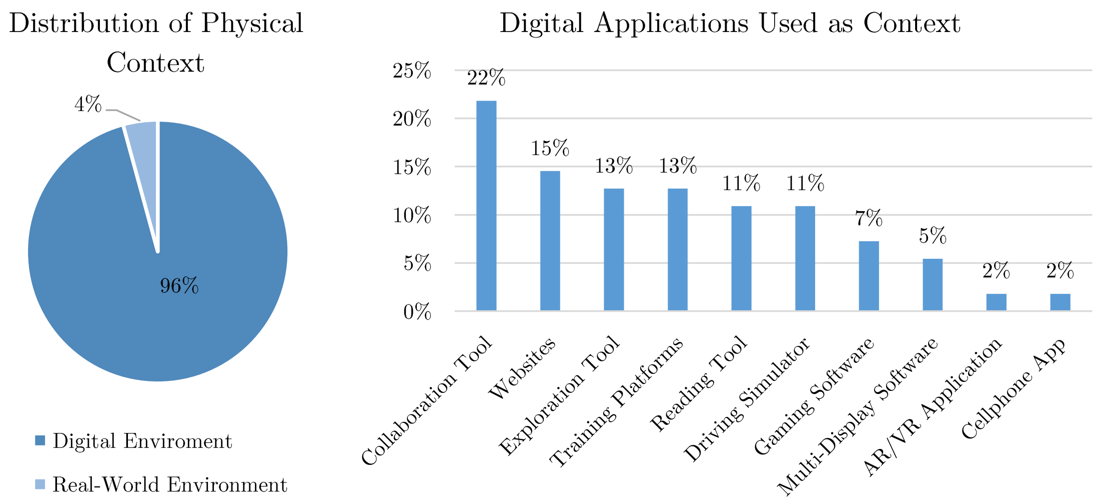


Figure 3.6.: Descriptive statistics: physical context.

Task

Figure 3.7 displays a list of tasks and distribution of them investigated in the collected papers. As can be seen, browsing and search tasks have the highest rate, with 45% of all tasks. This includes browsing or searching for a target on a digital platform or real-world environment. The reason for the high investigation of this task can be the user difficulties in managing limited attentional resources and facing different attentional breakdowns. Besides browsing and search tasks, researchers considered reading (15%), driving (11%), learning (11%), and monitoring (6%) tasks. I assume that the need for having proper attention allocation while conducting all those tasks is the main reason to select them in eye-based IIS studies. Examples of such support are informing users about mind-wandering status while reading a text, notice all critical information while driving, concentrating while learning a new language, and avoid missing changes while performing monitoring tasks using multi-display environments. Furthermore, few studies focused on specific tasks such as remote physical tasks (4%), gaming (4%), writing (2%), and programming (3%). These tasks may not be as complex as others, but I found that most of those tasks are combined with collaboration tools and considered as a collaborative task, which increases the overall complexity.

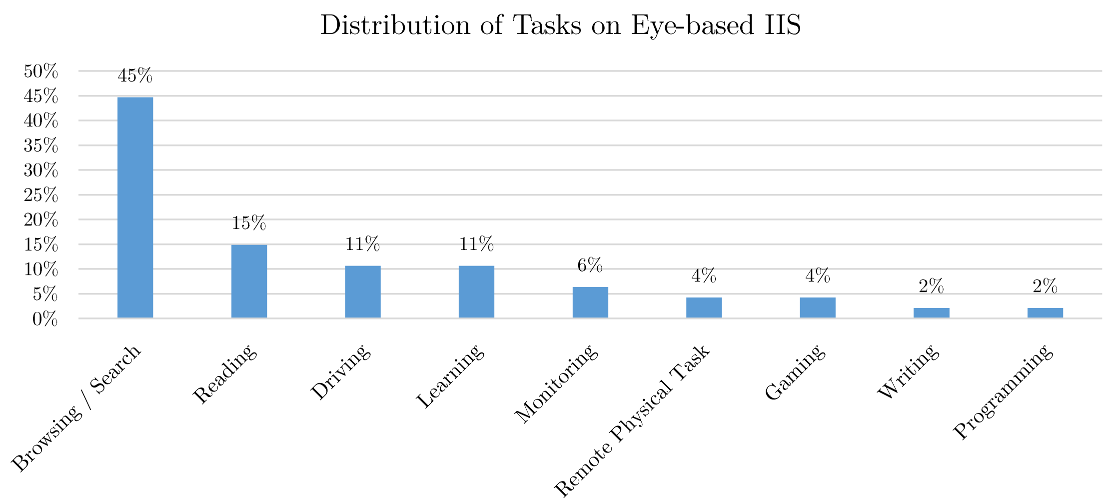


Figure 3.7.: Descriptive statistics: tasks.

Eye Tracking Technology

Figure 3.8 shows the distribution of apparatus types used in the collected papers. More than one eye tracker type is used in some studies, so I present the numbers in the percentage format. As can be seen, desktop-mounted eye trackers (71%) are more used than head-mounted (17%) eye trackers in eye-based IIS studies. I assume that the focus on the digital environment, lower price, easier setup, more manageable data analysis, etc., are some of the reasons for the higher usage of desktop-mounted compared to the head-mounted versions. Besides these two types, 8% of the used eye trackers are webcam-based devices. In this type, researchers used either the existing algorithm that converts webcams to eye tracking (e.g., OpenGazer) or developed a specific algorithm. As another apparatus type, a few studies used VR headsets equipped with eye trackers (2%) or smartphone cameras (2%). The reason for the low number of VR-based eye trackers may be that this technology is still rather new. Moreover, for smartphone cameras, the small displays and low accuracy level of algorithms to change cameras to eye trackers makes the usage of them difficult.

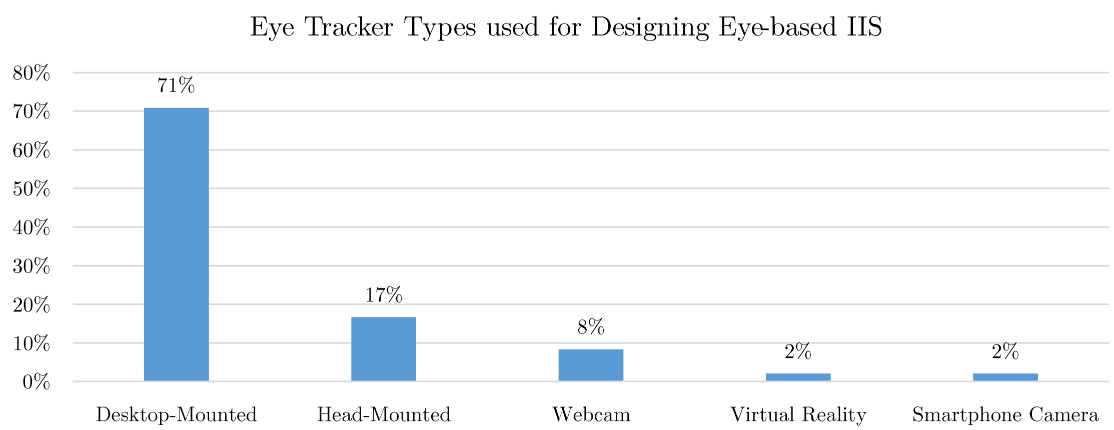


Figure 3.8.: Descriptive statistics: eye tracking devices.

Figure 3.9 presents the distribution of used apparatus among existing eye tracking hardware companies in the market and their products. As can be seen, there are 26 different apparatus types used in the collected studies. 23 of them are either the existing infrastructure in the market or used the existing algorithms to convert webcams to an eye tracker; the remaining 3 developed specific technologies. Among the existing eye tracking companies in the market, Tobii is the leading company for designing eye-based IIS. The results show that 53% of all papers used one of the products from Tobii while the other 47% of the apparatus are coming from various companies or are self-made solutions. Also, there are only six apparatus among existing 26 devices that are used more than three times in the collected studies: Tobii T60, Tobii EyeX, Tobii X120, Tobii Tx300, Tobii 4C, and EyeLink II. Therefore, I assume that these devices are the most popular devices among researchers for designing eye-based IIS. The remaining 20 apparatuses are used less than two times, which reveals that researchers tested different types of eye trackers during last years, and only a few eye trackers could receive more attention for designing eye-based IIS. Also, Tobii 4C eye tracker is the successor of Tobii EyeX; both are considered as low-cost eye trackers designed for eye-based interaction purposes. Researchers used these devices eight times in total during the last years, and I assume that they are more popular apparatus for designing eye-based IIS than the others.

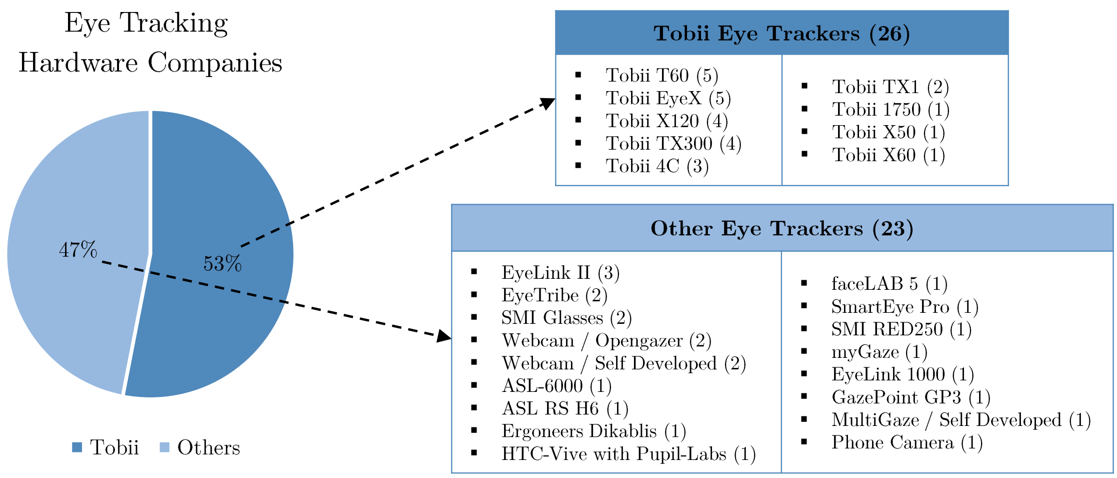


Figure 3.9.: Descriptive statistics: eye tracking hardware providers.

In previous eye tracking studies, researchers argued about the high price of apparatus and the difficulty of executing large-scale experiments. Based on the report from Farnsworth (2019), an average eye tracker price is around $17,500. However, during the last years, the eye tracking hardware companies released cheaper apparatus. I categorized the used apparatus in the collected papers by considering eye trackers lower than 1000$ as a low-cost eye tracker. This categorization is similar to the categorization from Farnsworth (2019) about the price of eye trackers in the market. In this study, I consider the devices with a higher price than that as high-cost eye trackers. Figure 3.10 reveals the distribution of low and high-cost apparatus as well as their usage in the last years. As can be seen, 43% of collected studies employed low-cost eye trackers, while 57% of the studies used high-cost eye trackers for designing eye-based IIS. However, checking the distribution of those eye trackers during the last years reveals that the usage of high-cost eye trackers decreased, and more studies with low-cost eye trackers are published. This shows that the tendency of researchers to use low-cost eye trackers for designing eye-based IIS started in recent years, and I assume that it continues in the future. The reason for that can be the improvement in the quality of low-cost eye trackers and their reliability in measuring eye movement metrics in real-time as well as the possibility of running cheaper studies.

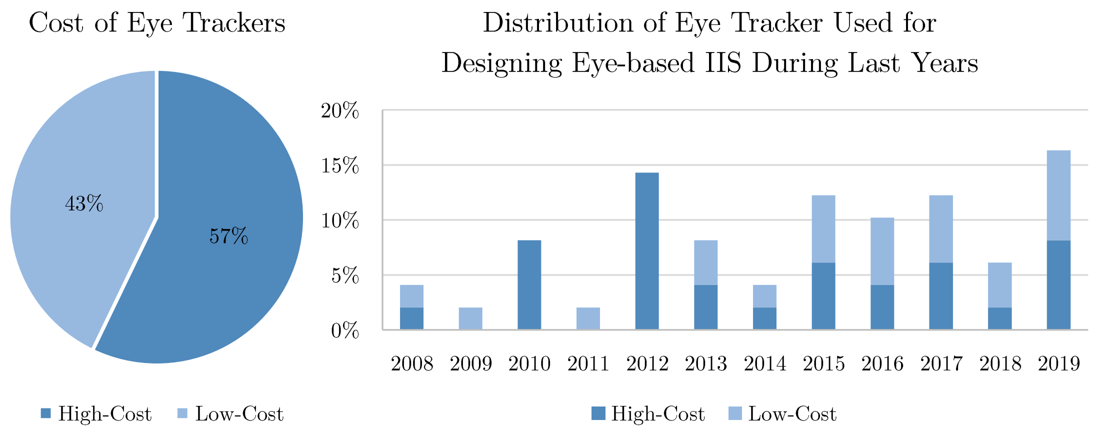


Figure 3.10.: Descriptive statistics: eye tracking technology prices.

Experimental Setup

As can be seen in Figure 3.11, most studies (96% of all) focus on the controlled lab environment to evaluate their system and only 4% tested their system as a field study. The reason for that goes back to the general difficulty of running eye tracking experiments as field studies independent in all forms include eye-based IIS, eye-based interaction, or for diagnostic purposes. In the eye tracking field studies, researchers have various challenges such as managing calibration, privacy issues, storing a large amount of eye movement data in long term usage, the difficulty integrating the devices to the real-world environments. These challenges are less while conducting a laboratory experiment in a controlled environment.

Furthermore, by analyzing the type of study design, I observed that more studies focused on a within-subject study type (42%). Conducting eye tracking studies requires much individual preparation that makes the experimental duration long. Also, the eye movements of users depend on several individual characteristics that are difficult to control and make the within-subject experiments more reliable with low amounts of participants. Furthermore, 31% of the studies are conducted as a between-subject design that shows this type is also popular among researchers. Also, 17% of the studies used a single user or group to test their system and did not compare the user or system's performance with any other conditions. Finally, few studies leveraged a mixed design (6%) or case study (4%) research approach. Therefore, I can see that researchers preferred to execute the experiment in a within-subject or between-subject manner rather than any other type while testing eye-based IIS.

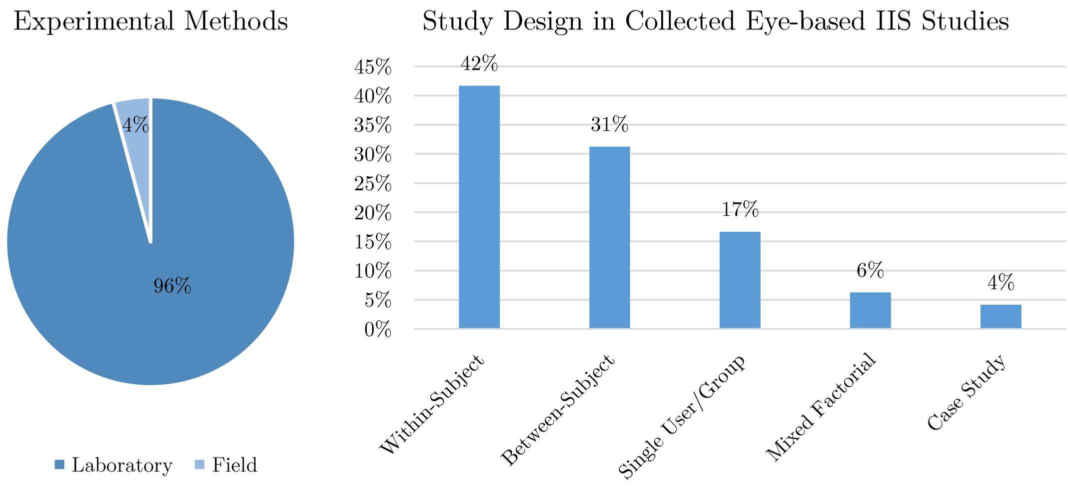


Figure 3.11.: Descriptive statistics: experimental design.

Besides, I also extracted the number of participants in the collected studies. The results are depicted in Figure 3.12. I found that the number of participants increased slightly during the last years. The average number of participants from 2008 until 2013 (M=20.68, SD=14.19) was lower than the average number of participants from 2014-2019 (M=34.46, SD=33.29). I assume that with cheaper and more reliable low-cost eye trackers; researchers also had a chance to included more participants in their studies. Having a higher amount of participants support the reliability of their findings.

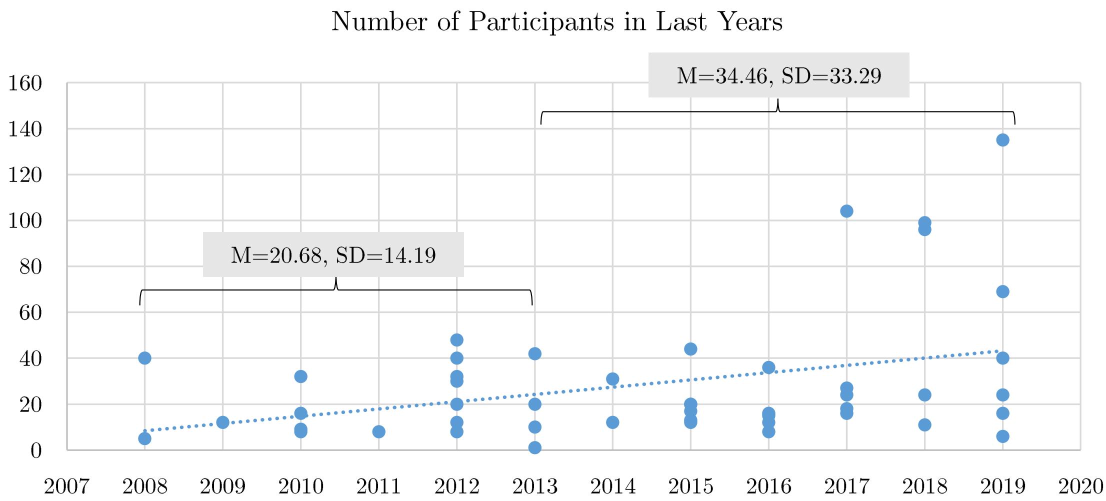


Figure 3.12.: Descriptive statistics: number of participants.

3.4.2. Eye-based IIS Properties

Eye-based IIS properties are at the core of the integrated conceptual framework explained in Section 3.2. In the following, I first discuss specific aspects for sensing and reasoning dimensions by presenting results from eye tracking metrics and model user stats. Later, I investigate the focus of the designed eye-based IIS system in the collected papers.

Eye Tracking Metrics

In this section, I focus on the eye tracking metrics used in designing eye-based IIS. Figure 3.13 shows the distribution of identified metrics in the collected papers. As discussed in Section 3.2, I identified five categories for eye tracking metrics: fixation-based, gaze-based, saccade-based, pupil-based, and others. Since eye trackers provide several measures simultaneously, some studies used more than one measurement while designing eye-based IIS. Overall, 89 measures (19 unique measures) are used in the collected papers. In order to avoid any confusion when identifying the preferred category, I present the results in percentages.

The most common eye tracking metric in designing eye-based IIS is the fixation-based metric (45%). When users are asked to conduct a task using their visual system, they first move their gaze to the relevant information; later, the visual system of the brain needs to be activated through a longer fixation of gaze to recognize an object properly that is consider as fixation (Majaranta and Bulling, 2014). Fixations are characterized through pauses of at least 100 ms and are, on average, between 200 and 600 ms (Majaranta and Bulling, 2014). Fixation position is the most common measure in this category (15%). Furthermore, the number of fixations (13%) and fixation duration (10%) in an Area Of Interest (AOI) is also measured by researchers in this category. This measurement can be used for different purposes, for example, interpreting more fixations and long duration of fixation on an AOI shows that this AOI is mostly related to deeper processing, more complex, less user-friendly areas, etc. On the opposite side, high stress can result in short fixation duration and expertise, which may prolong the duration (Holmqvist et al., 2011). Furthermore, some studies consider the last fixation points (6%). Recording the last fixation point is needed for TRS systems. In this case, the system records the last point of the users before the interruption and provides support when the user wants to resume the task by showing this position as a reminder for the last processed position. Also, one study used the first fixation point (1%) of users to improve the quality of their recommender system (Cheng et al., 2010).

The gaze-based measures are the second popular eye tracking metric (33%) and focus on the collected gaze data of users while working with eye-based IIS. The most commonly used measure in this metric is the gaze position (16%). In this measure, researchers focused on the position of the user gaze and related it to the point of relevance, interest, importance, etc. This can be seen as a fixation position; however, since researchers did not mention it specifically as a fixation point, I consider the gaze position as a separate measurement for the evaluation. The second measure is gaze duration (6%) that delivers insights on the period, the gaze enters an AOI, till the exit. A high value of gaze duration can indicate uncertainty, interest, and difficulties in extracting information, etc. This measure can also be relevant to fixation duration. The next measure is mutual gaze (4%), which is covered in some collaboration scenarios and determines the level of joint attention between partners. Furthermore, researchers investigated the number of gaze transitions (2%) that associates with the movements between two AOIs. Also, in some cases, researchers identified the presence of the users in front of the computer by tracking their gaze presence (2%). Besides, researchers tracked the gaze data to check if an AOI is entered several times and consider it as the user visit counts (1%) within this AOI. One study calculated the 3D focal depth of eye gaze (1%) using online gaze data to calculate when uses attention is engaged in a virtual display space while wearing AR glasses (Toyama et al., 2015).

Besides fixating, users constantly scan the visual environment with the eyes through fast eye movements, called saccades. Saccades are *"rapid motions of the eye from one fixation to another"* (Holmqvist et al., 2011, p.23) and saccade-based measures shall *"indicate the quality of visual cues in the stimulus or extent of visual searching"* (Kurzhals et al., 2016). This metric covers 8% of all studies and is less popular than fixation and gaze-based metrics. However, it offers the possibility to identify difficulties with the encoding of visuals by measuring a number of the saccade (3%) or lack of engagement by saccade length (2%). Also, they provide insights into the mental workload (Holmqvist et al., 2011, p.405). Furthermore, the direction of the saccade (2%) can support the system for identifying the user intention (e.g., switch line while reading when the saccade is from top to down)

The next metric is the pupil-based that only covers 8% of the collected studies. The reason for that can be the pupil's sensibility to the light and distance, which makes it challenging to use it out of a controlled environment. Researchers that used this metric consider two measurements include pupil dilation (7%) and dilation speed (1%) as two measures. The pupil diameter is used to measure the user's cognitive load, which is higher for a bigger dilation (Holmqvist et al., 2011, p.393). Pupil dilation can also be a measurement to indicate a user's interest; a larger diameter leads to greater interest. Apart from this, other external factors as diabetes, ages, pain, drugs, or emotion tend to influence the pupil size as well. Also, Vrochidis et al. (2011) used the speed of dilation as the rate of changes in time and considered it as an indicator of interest.

Besides the mentioned category, some papers used the scanpath measure (3%), which combines fixations and saccades of the users. It explains the sequential order of the fixations on the underlying stimulus. Following the path can be interesting to discover the user interactions with the interface. The scanpath is useful when the research concerns the time until an area is first entered. Furthermore, it explains difficulties in handling the task by the user. Beside scanpath, 3% of the studies extracted several eye relevant features and used a mixture of those to model user behavior. This approach is called as *"global eye feature"* by D'Mello et al. (2017). In this study, the authors used 62 global eye features to identify the mind-wandering status of the users while reading a text.

Analyzing the results shows that considering gaze and fixation based metrics is the most common metric (78% in total). Regarding the measures, gaze and fixation positions were popular among researchers rather than any other measure (31% in total).

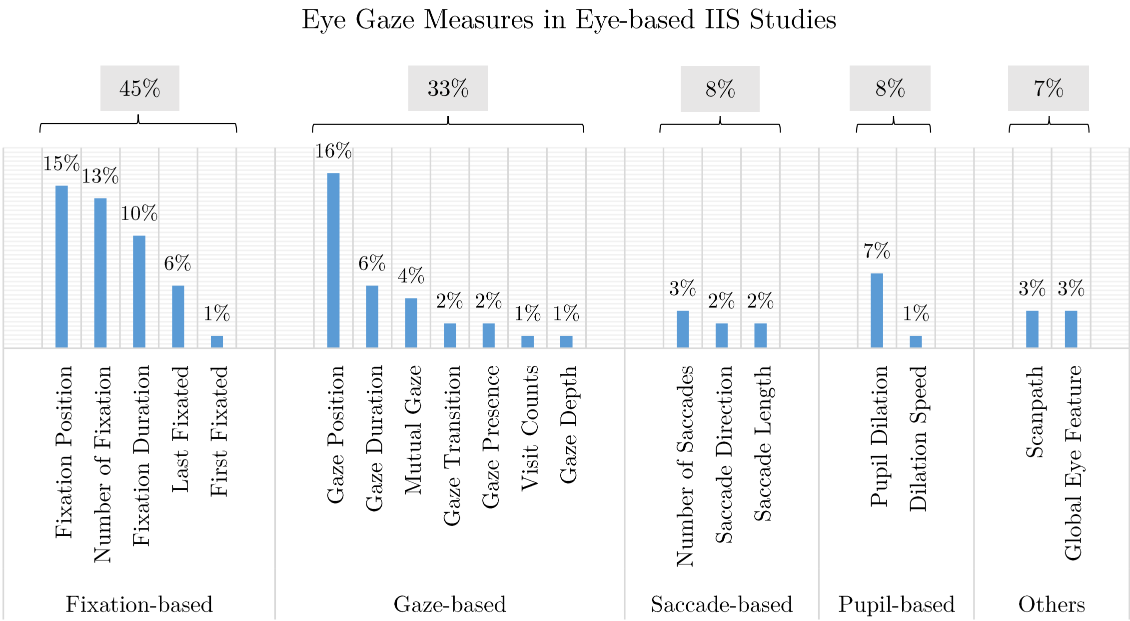


Figure 3.13.: Descriptive statistics: eye tracking measures.

Reasoning

Figure 3.14 shows the list of user states identified through collected eye movement data. Researchers mainly detected user distribution of attention in a given context and task that is a proxy for relevance or interestingness for the user. Therefore I can see that most eye-based IIS studies are in the direction of AUIs, attention-aware systems, and pervasive AUIs as discussed in Section 3.2.1. The second popular usage is the detection of attention shifts (13%). This identification used to support users when they face an interruption or need to shift their attention in multi-display environments. Next, identification of the engagement (8%) and mind-wandering (5%) are investigated with some eye-based IIS. Last, only a few studies focused on intention 3%, uncertainty 2%, and confidence 2%.

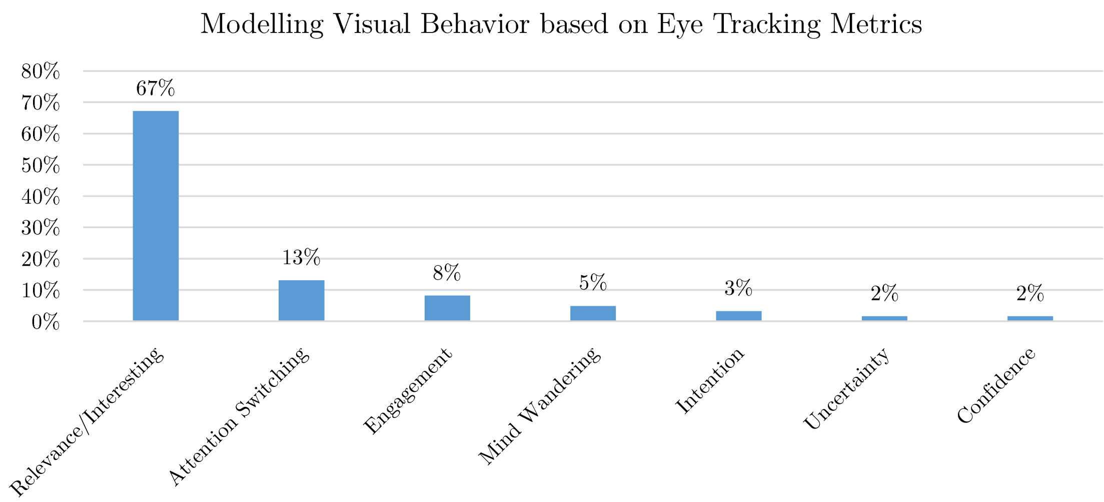


Figure 3.14.: Descriptive statistics: modeling user states.

Eye-based IIS Focus

Figure 3.15 shows the distribution of eye-based IIS focus among the collected papers. As can be seen, I found that the papers are almost equally distributed among system and user adaptation focuses. 51% of the collected papers focused on system adaptation by providing implicit feedback to the system, while 47% of them focus on user adaptation by increasing user awareness and providing corrective feedback. Furthermore, one study (2%) covered both focuses by providing different types of innovative interactions using user's real-time eye movement data. This shows that the research stream on both directions is receiving attention by researchers in the field of eye-based IIS and is properly balanced. Furthermore, I analyzed these two focuses based on years of publication. I found that in the first years, researchers focused more on system adaptation. However, during the last years, focusing on using user's eye movement data for user adaptation is increased.

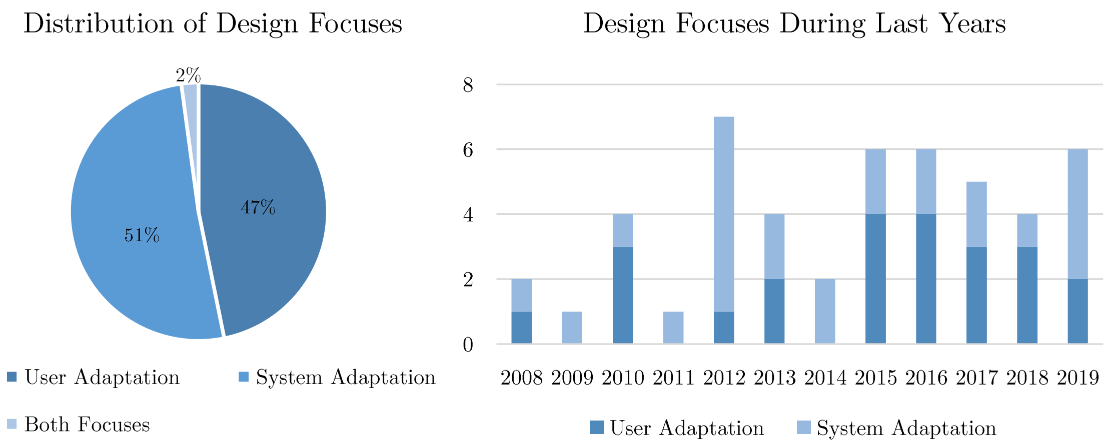


Figure 3.15.: Descriptive statistics: focus of eye-based IIS.

3.4.3. Outcome

Perception Outcomes

By analyzing the collected papers, I found that only 60% of the studies collected user perceptions, and 40% ignored it. Researchers used survey questions or interviews to collect user opinions after they experienced the designed eye-based IIS. As a result of this, I identified 12 different perception constructs and measurements leveraged in the collected studies and present them in Figure 3.16. The findings show that perceived usefulness (33%) is the most popular construct to measure while analyzing user perceptions. Furthermore, researchers collected perceived satisfaction (17%) of the users. These two constructs cover overall 50% of all collected measures. The high frequency of using these constructs shows the high importance level of them for the eye-bases IIS designers. The remaining 50% comprises ten other constructs. Some researchers tried to capture the mental workload (10%) of the users while working with eye-based IIS by conducting the NASA-TLX test, asking survey questions, or conducting an interview. Besides, researchers that focused on designed collaborative systems with eye trackers asked participants about the collaboration quality (10%). Also, researchers asked about distracting levels (8%) of the provided feature with eye-based IIS. Some researchers collected ease of use of the system (6%). Also, 4% of the studies checked whether the tracked eye movement data was correct or not based on what users remember about their attention distribution. The measures like confidence (2%), frustration (2%), challenge (2%), fun (2%), and nervousness (2%) were also integrated into some studies.

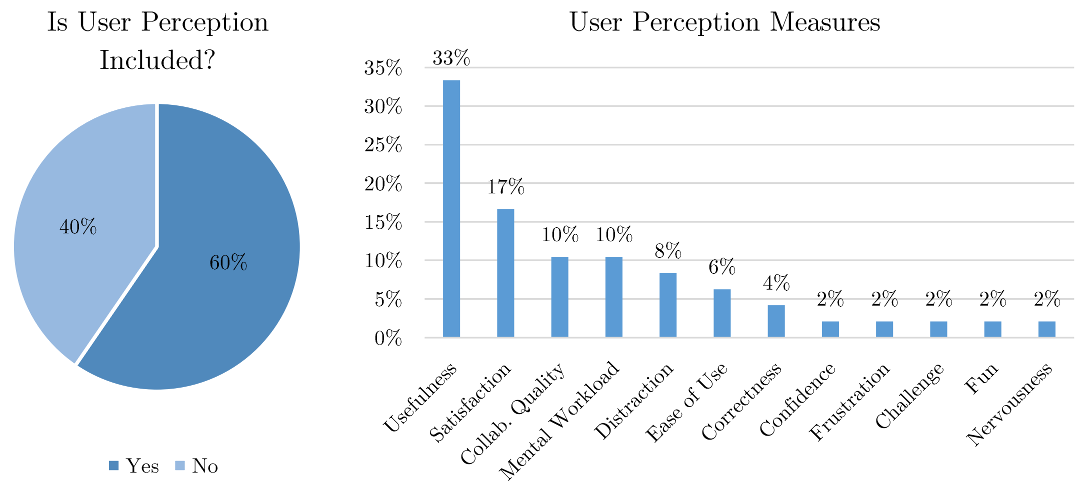


Figure 3.16.: Descriptive statistics: user perceived outcomes.

Behavioral Outcomes

By investigating the collected papers, I found that 57% of the collected papers include the user behavior in their evaluation section, and the remaining papers ignored it. This distribution is almost similar to the perception outcomes. However, only 36% of all papers both measure user perception and behavior. 21% only did the behavior and did not include any perception measures. 23% focused only on the perception of the users and ignored analyzing the behavior, while 19% did not include any of them. As can be seen in Figure 3.17, I identified 12 specific constructs for measuring user behavior. Since the eye trackers are used in designing eye-based IIS, it is dominant for tracking user behavior with 82% of all constructs. Researchers used eye trackers in the evaluation phase for different purposes including the user's attention allocation (29%), attention shift (11%) engagement (9%) search strategy (7%), gaze overlap in conversations (7%), global bias (2%), changes in attitude (2%), reading speed (2%) and resumption lag (2%). Moreover, some of them checked the user pupil data to measure the workload (9%). Besides eye trackers, 9% of the measures are related to the collected interactions through mouse and keyboards. Also, 9% of them analyzed the conversation between users in collaborative scenarios by checking the content of the user discussion.

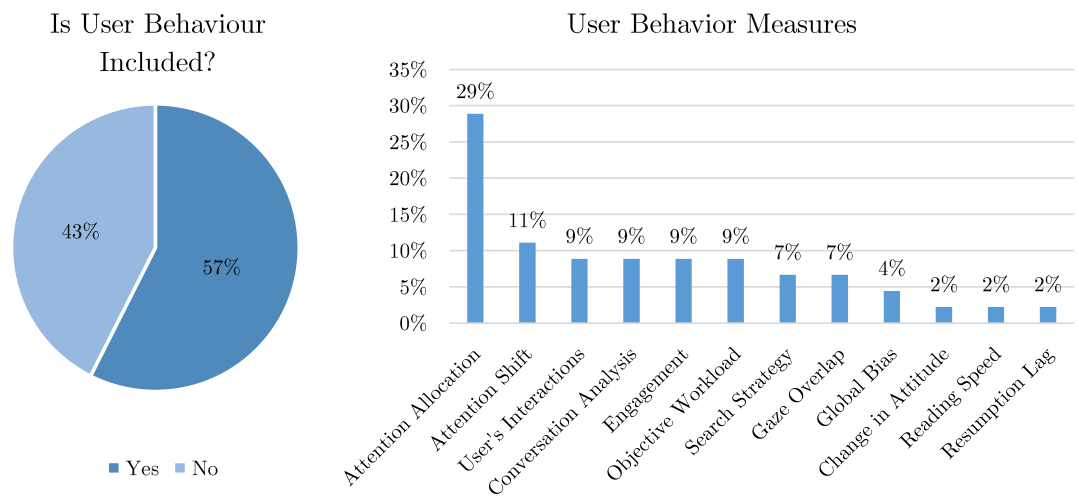


Figure 3.17.: Descriptive statistics: behavior outcomes.

Performance Outcomes

Based on the collected papers, 75% of the studies focused on measuring the user's performance. I found them most papers include user performance besides behavior or perception. 49% of them involve both the user performance with behavior, and 51% involve perception with it. Only 30% of them measured all three outcomes include perception, behavior, and user's performance.

As can be seen in Figure 3.18, I identified seven constructs for estimating user performance. Among the constructs, the accuracy and completion time are the most popular measures with 66%. The accuracy is considered as the measure to show how the users were successful in conducting the assigned task. Accuracy is the most popular measure, with 40% of all measures for user performance. Completion time is considered the measure to show the speed to conduct the assigned task. This measure received 26% of all measures for user performance. In addition to these two measures, some researchers considered the reaction time (11%), comprehension (9%), self-reported measure(6%), driving performance (6%), and effectiveness(2%) as other methods for measuring the user performance.

Regarding the system performance, only 32% of the studies included this dimension. The reason for the difference between popularity to measure the user performance and the system performance has roots in two different focuses on designing eye-based IIS that I discussed in Section 3.4.2. Studies focus on user adaptation more involved in measuring user performance; however, the papers with system adaptation focus considered the system's performance as well. Also, I found that only 15% of the papers considered both user performance and the system performance in their reports. As can be seen in Figure 3.19, I identified three factors for measuring the system performance in which the system's accuracy is the most popular measure with 81%. Furthermore, few researchers considered how the system's running time (13%) was affected, besides how it could affect network traffic (6%).

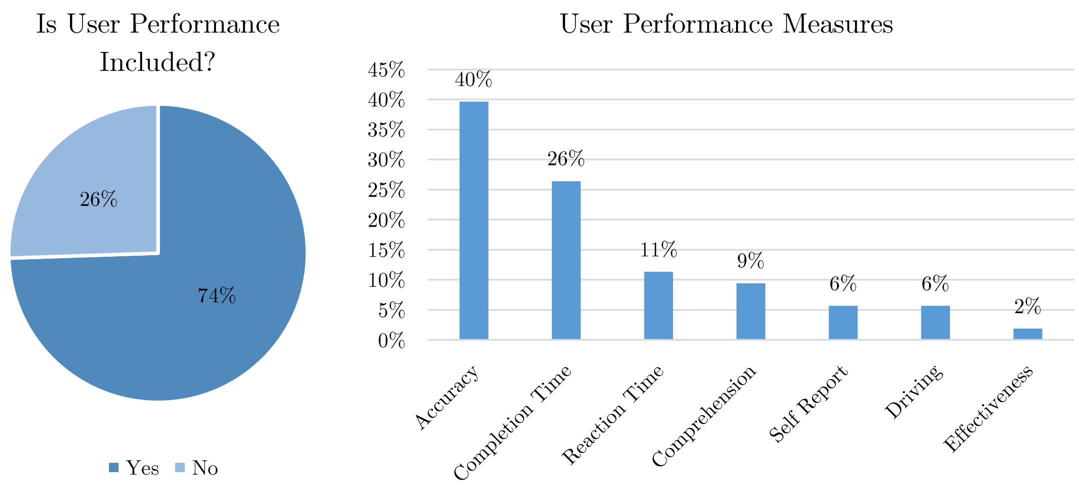


Figure 3.18.: Descriptive statistics: user performance outcomes.

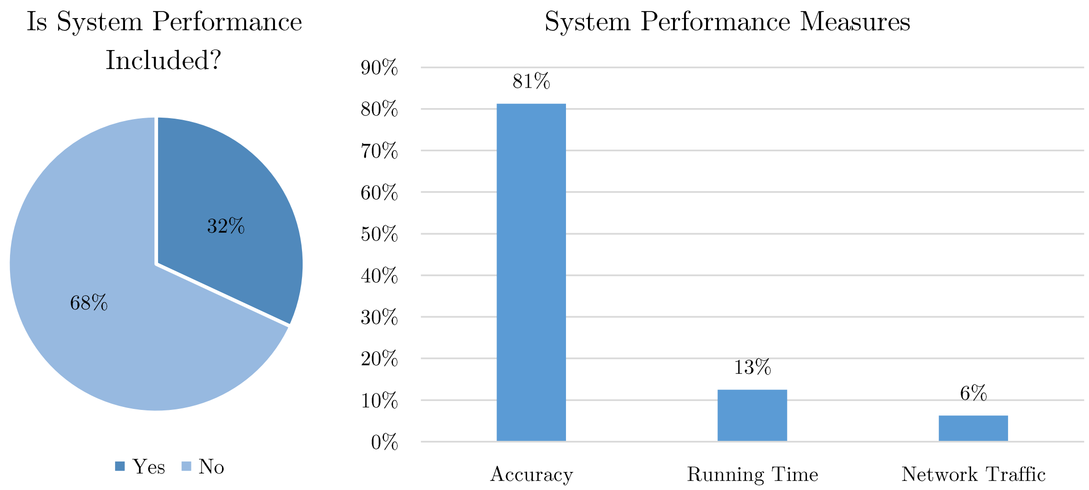


Figure 3.19.: Descriptive statistics: system performance outcomes.

3.5. Discussion and Future Research Directions

Analyzing the state-of-the-art along the dimensions of the conceptual framework supports in identifying the status quo and potential research gaps. In general, I conclude that besides the well-established usage of eye trackers for understanding user cognitive processes by analyzing their eye movement data in an off-line mode, there is an investment in using them in real-time. Particularly, more recently, there has been a growing interest in sensing the user's eyes, derive user state in real-time, and designing eye-based IIS that focuses on either system or user adaptation. Although the results show progress in this field during the last years, I believe that there are interesting research gaps that could be approached by researchers. In the following, I discuss the status quo and the suggestions for future research directions along with the findings by analyzing dimensions in three major categories of the conceptual framework: 1) influential factors 3.4.1, 2) eye-based IIS properties 3.4.2, and 3) outcomes 3.4.3. Table 3.1 presents the suggestions for future research directions for eye-based IIS.

Influential factors	**Context and Task**	• Increase research on team-level eye-based IIS and go beyond dyadic settings. • Investigate eye-based IIS interactions between users and agents in team settings. • Broaden research emphasizing the role of more specific user characteristics and design user-adaptive eye-based IIS. • Investigate eye-based IIS beyond well-defined, restricted environments. • Design eye-based IIS for enterprise environments (professional tasks and applications). • Go beyond established monitor displays and investigate eye-based IIS for AR, VR, mobile and tablet users.
	Eye Tracking Technology	• Leverage more user-friendly eye trackers (e.g., no calibration, lighter, smaller, etc.) for eye-based IIS. • Design privacy-aware eye tracking technology. • Integrate eye trackers into VR and AR devices. • Deliver cost-effective eye trackers, including advancing algorithms for converting webcam and mobile phone camera data to be leveraged for eye tracking.
	Experimental Setup	• Go beyond lab experiments and conduct field studies with eye-based IIS. • Conduct online experiments with eye-based IIS using crowdsourcing. • Increase the sample size in the experiments in order to deliver more generalizable findings.
Eye-based ISS Properties	**Sense and Reasoning**	• Integrate and test eye gaze metrics. • Investigate the combination of eye gaze metrics. • Investigate short terms user states such as emotion and stress. • Investigate long term user states such as gender, personality, WMC, etc. • Combine eye trackers with other users' input resources such as face recognition and biosignals (heart rate variability), EEG, or FMRI.
	Eye-based IIS Focus	• Intensify research on providing corrective feedback and increase user's awareness. • Test providing corrective feedback for further contexts and tasks. • Solve usability issues with corrective feedback in eye-based IIS. • Individualize corrective feedback.
Outcomes	**Perception and Behavior**	• Standardize reporting about users' perceptions and behavior. • Analyze users' behavior measures based on users' eye movement data. • Establish evaluation frameworks for perception and behavior measures. • Leverage further data resources to understand user states better while working with eye-based IIS.
	Performance	• Emphasize analyzing system performance in future research. • Compare eye-based IIS performance with other attention detection techniques (e.g., mouse-based detection).

Table 3.1.: Summary of future research directions based on identified perspectives.

3.5.1. Influential Factors

Contexts and Tasks

Findings in the context analysis presented in Section 3.4.1 show that both individual and team levels received attention by researchers. However, the amount of research on the individual level is much higher than on the team level. Thus, there is a need to conduct further research in a team-level direction. Besides, I found that most existing team-level studies focus on a dyadic setup while, in reality, there are many remote meetings with more than two users and more complex interactions among participants. Therefore, I suggest investigating eye-based IIS systems beyond dyadic settings and focus on designing systems that include more users. Additionally, the interaction between users and agents received less attention in existing research. This interaction can be in dyadic settings with collaboration between one user and the agent or considering an agent as one participant in a setup with more than one user. Also, I suggest considering further user characteristics beyond age, gender, previous experiences, and vision status. Users of eye-based IIS can also be characterized by WMC, personality, reading speed, etc. Individual differences can strongly influence the effectiveness of an eye-based IIS, and it may be necessary to adapt eye-based IIS accordingly. More specific user characteristics can be collected by using survey-based approaches or using user's eye movement data to predict certain user characteristics. Recently, this research direction received more attention in the eye tracking community however they are not integrated with an eye-based IIS focus (Al-Samarraie et al., 2018; Berkovsky et al., 2019; Conati et al., 2017; Hayes and Henderson, 2018; Hoppe et al., 2018; Raptis et al., 2016; Toker et al., 2013). I believe that having a deeper look into more specific user characteristics and designing user-adaptive eye-based IIS is an interesting avenue for future research. Regarding the physical context, existing studies are mainly conducted while users engage with digital applications in well-defined, restricted environments rather than in open environments. However, eye-based IIS usage, especially with head-mounted devices, can be used in more open environments such as driving a car, working with industrial tools, or teaching in classrooms. So far, in open environments, the use of eye trackers is mainly limited to collecting eye movements and understanding cognitive processes, and limited studies are focusing on providing eye-based IIS on this basis. Some researchers have emphasized that their eye-based IIS could be used in open environments. For example, Kern et al. (2010) have suggested exploring Gazemarks in the automobile context as interruption handling can highly improve safety.

Besides open environments, I also identified that integrated digital applications rarely include enterprise applications. In existing research, the focus is preferably on private usage, including entertainment, internet usage, online learning, etc. Therefore, I suggest investigating eye-based IIS at the workplace in combination with professional tasks and applications. For example, Tremblay et al. (2018) have called to include their approach in real-time operational support applications.

I expect the usage of eye-based IIS goes beyond desktop-based or open environment scenarios as well. First, with the increased usage of VR and AR technologies, I expect future research in eye-based IIS within these technologies. Combining VR and AR technologies with real-time eye movement data can support both system and user adaptation in the future. Second, I assume further research focusing on tablets, smartphones, smartwatches, etc. since users frequently use them in their daily life. For example, Cheng et al. (2018) have mentioned that their approach would be rather suitable on a smartphone for cross-application usage instead of a cross-device environment.

As context and tasks are tightly interconnected, I expect that by investigating new contexts for eye-based IIS, more tasks should be added to the list of tasks discussed in Section 3.4.1. However, the browsing and search task is assumed to remain the most common task because users have difficulties in managing limited attentional resources while facing a massive amount of information.

Eye Tracking Technology

As discussed in Section 3.4.1, the current focus of researchers is on the usage of desktop-mounted eye trackers that fit a well-defined, restricted environment. I assume that the use of different eye tracking technologies will increase by extending research to new contexts and tasks. For example, the usage of head-mounted eye trackers should increase by integrating open environments rather than working with digital applications. For that, there is a general need for more user-friendly eye trackers, with an easier or no calibration process, smaller and easier to carry, etc. Having proper devices can increase the adoption and usage of eye tracking technologies. Besides that, there is a need to integrate eye trackers as an embedded capability in VR and AR systems for designing eye-based IIS. Finally, an essential driver for adopting and using any eye tracking technology is the implementation of privacy features (Kunze et al., 2013; Steil et al., 2019).

Furthermore, future work should develop and evaluate cost-effective eye tracking technologies leveraging webcams. In order to achieve mainstream adoption of eye-based IIS, dedicated eye trackers are still expensive and not commonly available. Webcam and smartphone cameras have the potential to become reliable devices for algorithms to record and analyze gaze data through low-quality images. So far, several studies have focused on the reliability of low-cost and webcam-based eye trackers (Burton et al., 2014; Dalmaijer, 2014; Zugal and Pinggera, 2014), but the findings show that these eye trackers did not receive researchers' attention in the field of eye-based IIS.

Experimental Setup

As presented in Section 3.4.1, existing experimental studies mainly focus on controlled lab environments. As a future research direction, I suggest extending investigations on the usage of eye-based IIS in more natural environments. D'Mello et al. (2012) suggested testing their system in real-world computer-enabled classrooms. Mariakakis et al. (2015) also suggested testing SwitchBack in more natural surroundings. Alt et al. (2012) proposed to examine whether the approach applies to image-based content besides advertisement. Although such intention is already mentioned in most of the identified studies, the findings show that it is not investigated a lot so far. Furthermore, replicating existing eye-based

IIS studies in the field, reporting the results, and identifying new requirements would be interesting future contributions. Also, I assume that the average sample size for eye-based IIS studies is low. By extending the sample size, researchers could control for more specific user characteristics and ultimately deliver more generalizable knowledge. I assume that further improvement of eye tracking technology regarding cost-effectiveness and easier calibration processes would enable running experiments with a higher sample size. I assume that by improving webcam and mobile phone camera-based eye trackers, one could conduct large-scale online experiments by leveraging crowd-based services such as Amazon Mechanical Turk.

3.5.2. Eye-based IIS Properties

Sense and Reasoning

In general, as shown in Section 3.4.2, researchers have used a broad spectrum of metrics for designing eye-based IIS. However, future research could add additional sensing metrics, such as smooth pursuit movements or entropy. Also, only a few studies used a combination of eye gaze metrics, while in some studies, using this approach could deliver more reliable findings (e.g., identify mind-wandering studies (D'Mello et al., 2017)). Nevertheless, the metric or the used combination highly depends on which specific user states researchers aim to model. As discussed in Section 3.4.2, so far, the interest and relevance of information is the main goal of collecting eye movement data. However, this source of information can be used for further identification of user states. Furthermore, to increase the quality of findings in user cognitive states and needs, eye trackers can be used in combination with other data resources. As an example, some researchers mentioned to add input variables, especially face detection features, as a valid point for future work (Ishii et al., 2013; Nguyen and Liu, 2016; Tremblay et al., 2018; Vrochidis et al., 2011). Roda and Thomas (2006) suggested using eye trackers beside biosignals like heart rate or EEG, brain signals with fMRI, etc.

Eye-based IIS Focus

As discussed in Section 3.4.2, existing research emphasizes on both user adaptation by increasing user awareness and system adaptation by increasing the intelligence level of the system. However, by analyzing the distribution of papers, I found that the number of papers focusing on user adaptation is slightly lower than designing intelligent technology. Further investigation shows that the number of papers in this direction increased during the last years. Thus, I suggest continuing the trend and ensure balancing both directions. Providing corrective feedback to the users can assist them in recognizing their failures and adapt them. This approach seems easier to be implemented and can be used in various situations than system adaptation. Furthermore, in this type of focus, users who are directly involved in interacting with corrective feedback and usability of such feedback are essential. There is a need to investigate different types of corrective feedback based on user characteristics, task, and context. For example, D'Mello et al. (2012) proposed to identify individual differences and adapt gaze-reactive statements depending on these differences as an essential focus of further research. Also, Akkil and Isokoski (2016) and D'Angelo and Gergle (2016) have noted that participants struggled to interpret sporadic eye movements; more research is also required for finding the best options. Some studies like Jo et al. (2015), D'Angelo and Gergle (2018) and Newn et al. (2017) have shown the interest of the community in finding the appropriate type of gaze-based highlighting method as corrective feedback; however, they are limited to a specific task, and it is not possible to generalize the results. Besides the representation of such corrective feedback, there is a need for further studies on how often and when eye-based IIS should provide feedback. For example, D'Angelo and Gergle (2016) considered a selective option for users to decide how often and when the gaze visualization is displayed as a need for further improvement. Also, researchers should investigate corrective feedback's personalization since the users may have different cognitive abilities that influence the effectiveness of corrective feedback.

Additionally, most eye-based IIS considered only one type of focus category. However, I suggest searching for synergies between the two paradigms. As eyes are the primary sense to process information while interacting with the environment, researchers can consider designing systems that integrate both implicit and corrective feedback. For example, Mariakakis et al. (2015) suggested implementing more features for SwitchBack, e.g., automatic scrolling when the user reaches the bottom of the text or magnifying glasses to enlarge the current read line of text.

3.5.3. Outcomes

Perception and Behavior

As discussed in Section 3.4.3 and Section 3.4.3, researchers leverage different measures for reporting user perceptions and behavior. It has been recognized that meeting user expectations is a critical success driver for eye-based IIS. However, I believe that the focus on systematically measuring these outcomes should increase in future research. 40% of the collected papers did not include any measures for perception. Knowing more about user perception and reporting it supports the research community in understanding the impact of eye-based IIS on the user and ultimately designing better systems. Delivering eye-based IIS aligned with user expectations is a critical factor for the mass adoption of this technology. Besides user perception, researchers in the field of eye-based IIS can use eye trackers that are integrated into the design procedure for the evaluation as well. Surprisingly, 43% of the collected papers ignored reporting user behavior. Therefore, I suggest providing information about user behavior in the field of eye-based IIS as a new standard in corresponding publications. Researchers can use the same approach to find user states to discover more about user behavior and include them in their findings. Therefore, there is a need to extend the leveraged behavior measures in future studies. Besides, I observed diverse approaches to collect perception and behavioral data by researchers. For perception, interviews and surveys are the most common way, but mixed methodologies such as think-aloud approaches and eye tracking can also be used to measure more accurate perception and behavior. Regarding the behavior, so far, researchers have focused on eye tracker and log data, however integrating further devices such as EEG, fMRI, and face recognition as advanced evaluation tools could be valuable. Finally, researchers collected perception data through various techniques. To create more accurate results, I suggest developing a framework and a standardized survey and interview protocols for future studies.

Performance Outcomes

As discussed in Section 3.4.3, I investigated performance from two perspectives: user and system performance. Most papers include user performance as the main goal of the eye-based IIS. The way to measure user performance is directly related to the user task. However, only a few papers analyzed system performance. Therefore, I suggest future research should include the system performance of eye-based IIS as well. In general, there is a need to establish a proper methodology for measuring and reporting this information. Furthermore, as there are different ways to compare the attention of users (through mouse movements, EEG, etc.), I suggest future research comparing the different algorithms used in eye-based IIS with other attention-aware systems. For example, Akkil and Isokoski (2016) suggested the future development of GazeTorch by comparing the algorithm with mouse-based pointing systems.

3.6. Summary

As Study I in this thesis, I presented the results of a SLR study focusing on eye-based IIS. This SLR study is based on the suggested approach of Kitchenham and Charters (2007) and covers papers from the beginning of 2008 to the end of 2019. Conducting this study before doing the DSR project support to identify different dimensions for designing innovative IS applications that integrate real-time eye movement data as suggested by IS researchers (Davis et al., 2014; Dimoka et al., 2012; vom Brocke et al., 2013). Furthermore, the identified papers and the results from the analysis serves as the related work for the design cycles and supports highlighting MRs and DPs. Especially the eye-based IIS application that focuses on increasing users' awareness in data exploration tasks and resuming an interrupted task.

By improving eye tracking technology using eye movement data in real-time as an input for designing IIS increased significantly in the last years (Chuang et al., 2019; Nakano et al., 2016). Eye-based IIS provides innovative interactions enabling advanced forms of system and user adaptation. However, existing studies on eye-based IIS are scattered, and there is a lack of a systematic overview of existing research in this field. This study contributes to the field of eye-based IIS by providing a conceptual framework for designing such a system. Later, building on the developed conceptual framework, 47 identified papers were analyzed in detail, and I presented the state-of-the-art of eye-based IIS. Also, I identified research gaps and outlined possible future research directions. Mainly, the results from context and tasks show that the studies rarely include enterprise applications. Additionally, I search the same search stream for this SLR study within a selection of journals in the IS community known as the Basket of 8 [3]. The findings show the lack of research on integrating real-time eye movement data for designing innovative IS applications. Eye tracking technology is known as the dominant tool for IS studies that integrated neuroscience tools (Riedl et al., 2017), but the focus is on using it for diagnostic purposes. These results are synced with the emphasis of researchers in IS field that there is a lack of research on integrating neuroscience tools such as eye tracking technology to design innovative IS applications (Davis et al., 2014; Dimoka et al., 2012; vom Brocke et al., 2013).

[3] `https://aisnet.org/page/SeniorScholarBasket`

4. Research Methodology [1]

4.1. Design Science Research

This thesis follows the DSR paradigm to deliver an innovative solution for real-world problems (Hevner et al., 2004). I mainly addressed two problems associated with limited attentional resources by designing attentive information dashboards with individualized VAF by integrating eye tracking technology. The first problem focuses on managing limited attentional resources during data exploration tasks. The second problem focuses on resuming interrupted data exploration task. I primarily address the lack of design knowledge for providing solutions that integrate user's eye movement data in real-time. I adapted the research approach from Kuechler and Vaishnavi (2008) and divided the entire DSR project into three sequential design cycles. In this DSR, I focus on artifact-centric approach (Peffers et al., 2007). The goal is to produce new knowledge by construction and evaluation of software artifacts (Kuechler and Vaishnavi, 2012). Figure 4.1 summarizes the three design cycles of the entire DSR project.

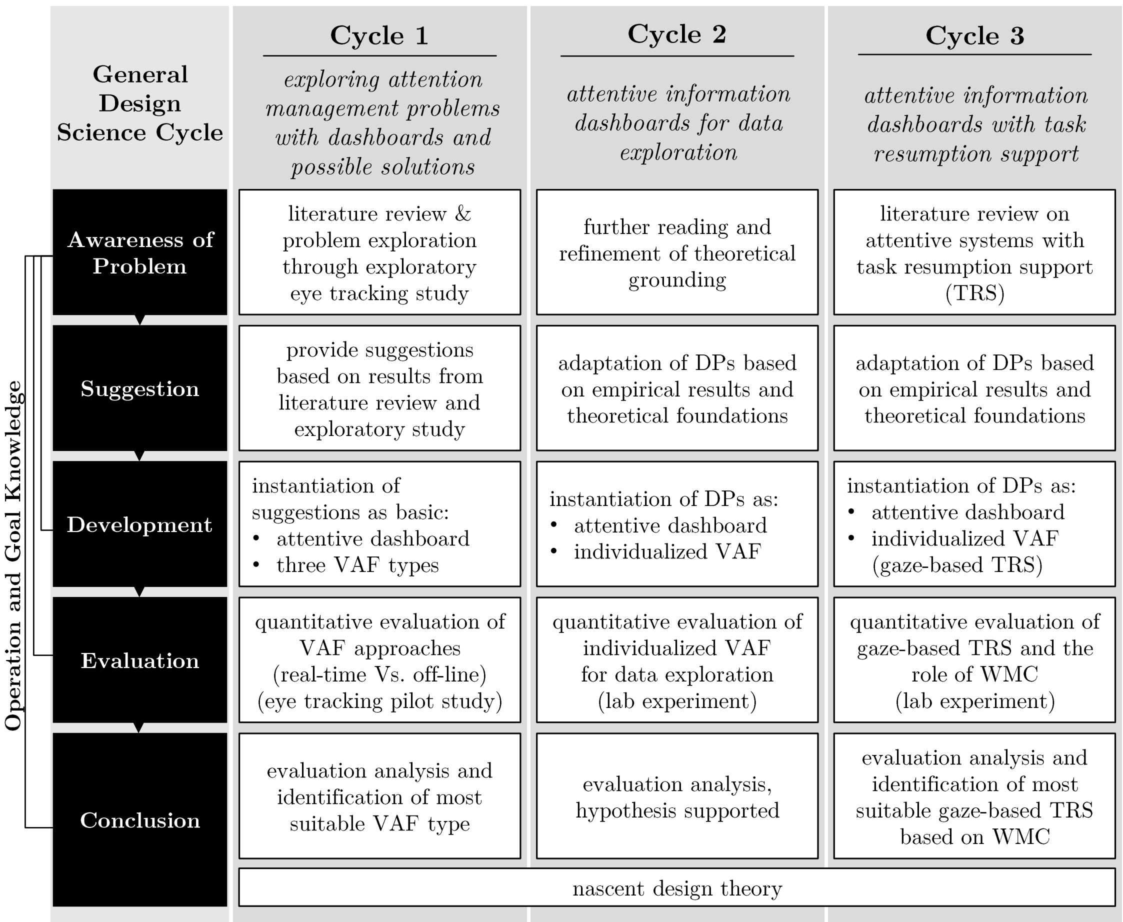


Figure 4.1.: Design cycles integrated in this thesis.

[1]This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini et al. (2018b), Toreini and Langner (2019), Toreini et al. (2020b), Toreini et al. (2020c), Toreini et al. (2020a)

At the end of this DSR project and after completing all three design cycles, I summarized the findings in the general contribution as nascent design theory (Peffers et al., 2007) following six core components of design theory suggested by Gregor and Jones (2007). Section 8.3 presents the nascent design theory for designing attentive information dashboards with individualized VAF.

4.1.1. Design Cycle 1

I started the DSR project with a problem awareness step. The most common way to perform this step is to conduct a literature review or perform empirical research in forms of surveys or interviews (Hevner et al., 2004). After conducting a literature review, I found that existing research focuses on the role of attention and memory on single visualized information (Healey and Enns, 2012). There is only limited research on the cognitive state of the users focusing on information dashboards and there is a call for more research in this area (Alberts, 2017; Bera, 2016; Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). Moreover, detecting problems relevant to attention and working memory through surveys and interviews is not reliable since users have subjective views and have limited abilities to judge the effectiveness of their visual behavior (Dimoka et al., 2012). Therefore, as Study II in this thesis, I designed an exploratory study as a controlled laboratory experiment and simulated the data exploration task using an information dashboard. I chose a data exploration task since, in real-world scenarios, decision-makers explore dashboards from time to time to get a better understanding of their business. Periods to revisit dashboards can vary between daily visiting once a week, month, etc. The primary goal of this type of data exploration is to thoroughly investigate all information and try to understand the current status of the business. In this case, having effective attention allocation can increase the information processing of the user. I integrated eye tracking to evaluate user's visual behavior in this task. The usage of eye tracking provides the opportunity to objectively examine the attention of the user by analysing the recorded eye movement data and uncovering existing problems regarding to limited attentional resources. Furthermore, the role of visuospatial WMC of the users in allocating attentional resources is investigated. Based on the findings, I proposed six initial MRs for information dashboards that consider limited attentional resources and working memory of users when performing data exploration tasks. These MRs are classified into two categories, synced with the two focuses for designing eye-based IIS proposed in the framework of the SLR study in Study I. The first category includes three MRs that focus on making the system more intelligent for adapting the dashboard's layout based on the limited cognitive capabilities of users. The second category includes three MRs that focus on the necessity of providing new interactive features to users and focus on user adaptation. These interactive features should support managing limited attentional resources by increasing user's awareness about their previous allocation of the attentional resources. The derived knowledge can be used for articulating DPs and designing innovative features for dashboards.

Subsequently, I focused on implementing the MRs in the second category in Study III and proposed several designs for VAF grounded in research on attention and self-tracking feedback. To reach this goal, I proposed alternative designs for information dashboards that can track user's attention based on existing knowledge in literature. I derived two approaches of VAF types that operate based on eye movement data. One of these approaches is including off-line eye movement data from previous users as VAF and the other using real-time eye movement data of the user to provide individualized VAF. After the development of both approaches, I designed and executed an eye tracking pilot study to investigate each approach's effectiveness. For that, I integrated three groups of users that used VAF types. The first group used general VAF by providing an example of good Attentional Resource Allocation (ARA) integrating off-line records of eye movement data from other users that did the same task on the same dashboard. The second group also received the off-line records of eye movement data from other users but with improper ARA. The third group received individualized VAF that has represented their actual ARA and individualized VAF. Later, I compared the effects of general and individualized VAF, and the findings reveal the positive effects of individualized VAF on information processing compared to general VAF types.

4.1.2. Design Cycle 2

In the second design cycle, I investigated the influence of individualized VAF as the suggested solution for the data exploration problem in more detail. I started by refining the theoretical grounding for designing individualized VAF. For that I refined the corresponding MRs in Studies II and III. Later I derived two DPs based on the proposed system architecture to map these DPs to design features. Later, I instantiated an improved version of the attentive information dashboard and individualized VAF as a running software artifact. Next, following the suggested methods to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012), I conducted a large-scale controlled laboratory experiment to assess the effectiveness of designed individualized VAF on users' ability to manage their limited attentional resources. In this experiment, I compared two design configurations with DPs activated (individualized VAF) and deactivated (general VAF with a text-based explanation about attention) based on the proposed research model and three hypotheses. The results from this study revealed that individualized VAF positively influences users' information processing by improving their ability to manage limited attentional resources. The results of this design cycle are captured in Study IV.

4.1.3. Design Cycle 3

In the third design cycle, I focused on the situation that information dashboard users are faced with interruptions while exploring information dashboards. In this case, users need to shift their limited attentional resources from the data exploration task (primary task) to a secondary task. There are many interruptions around employees in workplaces (Czerwinski et al., 2004; Mark et al., 2008), and they have difficulty to resume their primary task after finishing the interruption task (Hemp, 2009; Mark et al., 2005). Previous research has shown the need to provide attention management systems to support users in task resumption (Anderson et al., 2018). In this design cycle, I first conceptualized individualized VAF that supports resuming an interrupted task as, gaze-based TRS. I also presented dimensions that impact designing effective gaze-based TRS by analyzing previous research in the field of interruption and gaze-based TRS collected in the SLR study in this thesis as the Study 1. Based on that, I presented six MRs and three DPs for designing attentive information dashboards that support users' task resumption with gaze-based TRS. Later, I proposed the system architecture to map three identified DPs to the design features. For this study, I suggested three types of highlighting methods for gaze-based TRS as last point, heatmap and scanpath. Such gaze-based TRS works as a memory aid to remember previous visual behavior. For the evaluation part, I compared the effectiveness of provided DPs and designed gaze-based TRS with the situation that users do not receive such support. Following the suggested methods to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012), I investigated the role of WMC on the effectiveness of each highlighting method for gaze-based TRS in a large-scale laboratory experiment as an exploratory study. The findings suggest that gaze-based TRS, especially heatmap highlighting, is beneficial for low WMC users when face with short-term interruptions. Furthermore, users with high WMC may not need a gaze-based TRS for short-term interruptions.

5. Design Cycle 1: Attention Management Problems and Possible Solutions [1]

5.1. Study II: Overview

Based on Gartner–Magic Quadrant for BI&A systems, visualizing the information and presenting the results in a comprehensive way is known as a critical capability of BI&A systems (Sallam et al., 2017). The main purpose of information visualization is to support users in perceiving patterns, which can be used to build appropriate explanatory models and improve their performance (Purchase et al., 2008). Information dashboards typically include several visualized information in one screen, and users need to explore them at the same time and find relationships between them before making decisions (Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). Information dashboards include a lot of compressed and essential information that supports comparing different perspectives and making proper decisions. However, conveying the enormous amount of information presented by information dashboards combined with a complex cognitive task is challenging for users (Niu et al., 2013; Sedig and Pasob, 2013). Decision-makers need to manage to allocate limited attentional resources while working with information dashboards to avoid typical attentional breakdowns, such as missing important information (Roda, 2011).

Furthermore, WMC is known as one of the individual characteristics affecting decision making as the mental representation about the status of the business is created in the users' working memory (Davern et al., 2012). Working memory has an impact on building contemporary global models of cognition and is involved in many complex cognitive behaviors, such as comprehension, reasoning, and problem-solving (Engle, 2002). Researchers found that individuals have different types of memories (Atkinson and Shiffrin, 1968; Baddeley and Hitch, 1974). Visuospatial WMC is an important individual differences variable while processing visualized information (Bačić and Fadlalla, 2016; Healey and Enns, 2012).

As discussed in Chapter 1, Section 1.2, so far, there is limited research on examining the role of attention and working memory while exploring information dashboards. To improve information dashboard design, knowledge about how users act and which of their cognitive limitations affect their performance is essential (Haroz and Whitney, 2012; Niu et al., 2013). To the best of my knowledge, no study has investigated the role of limited attentional resources and working memory while using information dashboards. Therefore, in this study, I investigate users' control on the attentional resources with the help of eye trackers, as suggested by researchers in the IS community, to assess the impact of systems on users' information processing (Dimoka et al., 2012). I also examine the role of visuospatial WMC as a critical working memory type on ARA while users are exploring information dashboards. As the Study II of the thesis, this study aims to find requirements

[1] This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini and Langner (2019), Toreini et al. (2020b)

for designing more effective information dashboards by addressing the following question, as the second RQ in this thesis:

> ***RQ2:*** *What are meta-requirements for designing dashboards that consider users' cognitive limitations of attentional resources and working memory?*

As Figure 5.1 shows, this study focuses on understanding existing attention relevant challenges of information dashboard users within the problem awareness section of this DSR project. An eye tracking experimental research approach is chosen for the problem awareness step because of the high reliability of eye movement data in finding problems related to allocating attentional resources compared to self-reported data (Dimoka et al., 2012). Therefore, this study contributes to the IS community and especially information dashboard design for BI&A systems by identifying MRs for designing more effective dashboards. These MRs are used in the remaining steps of the first design cycle, as well as the next design cycles. In the following, I explain the prototype design for the experiment, and the experimental setup. Next, the results are presented to explore different aspects of allocating limited attentional resources. Finally, I derive several MRs that are suggested for designing more effective information dashboards for data exploration tasks based on the results from the experiment and existing research on this field.

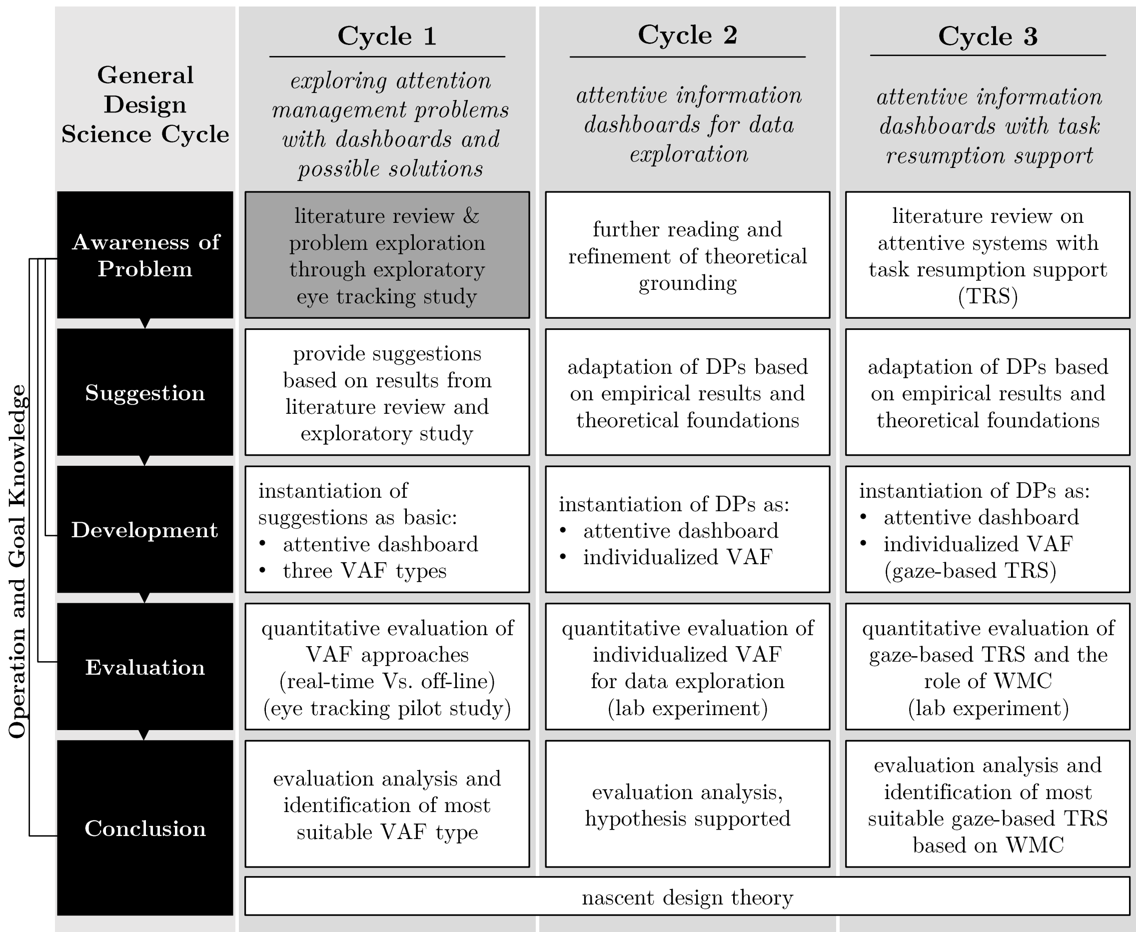


Figure 5.1.: The focus of Study II in this DSR project.

5.1.1. Laboratory Experiment

5.1.1.1. Experiment Design

The experiment was conducted in a controlled lab environment. As an apparatus, I used Tobii 4C eye tracker with sampling rate of 90 Hz and the relevant license to record and analyze the eye movement data. Figure 5.2 shows the stages of this experiment. The study started by calibrating the eye tracker with the Tobii Eye Tracking Core Software. After that, the screen-based instruction was given to the participants and followed by control questions. The introduction explained the different steps of the experiment and defined the keywords in the designed dashboard to ensure that all participants understood the concepts. Before starting the main part of the experiment, the participants were asked to look at a dot in the middle of the display for a few seconds to check if calibrations have remained stable or not. The experiment's task was designed based on a simulated business scenario in which participants were asked to imagine themselves as the sales manager who recently joined a company. In a few minutes, they will have a meeting with their boss and need to explain the business status of the company during the last six months. To get ready for this meeting, they need to explore the information dashboard for two minutes. This step is considered as the first phase (data exploration phase). The dashboard layout used in this study can be seen in Appendix B as Figure B.3 After the exploration, the participants were interrupted for 30 seconds and were asked to wait while they did not receive any extra information (Appendix B as Figure B.2). After the break, they revisited the same information dashboard for one more minute, which counts as the second phase of the experiment (revisit phase). Besides, the participants got a timer in the footer of the dashboard that informed the remaining time. The eye tracking technology measured the relevant gaze data from each user individually and was stored in a log file through the data exploration. After the experiment, participants had the chance to rest for a few minutes. Later, they joined a psychological test from the free PEBL test battery (Mueller and Piper, 2014) to measure their visuospatial WMC by the visuospatial Corsi Block-Tapping test (Kessels et al., 2000).

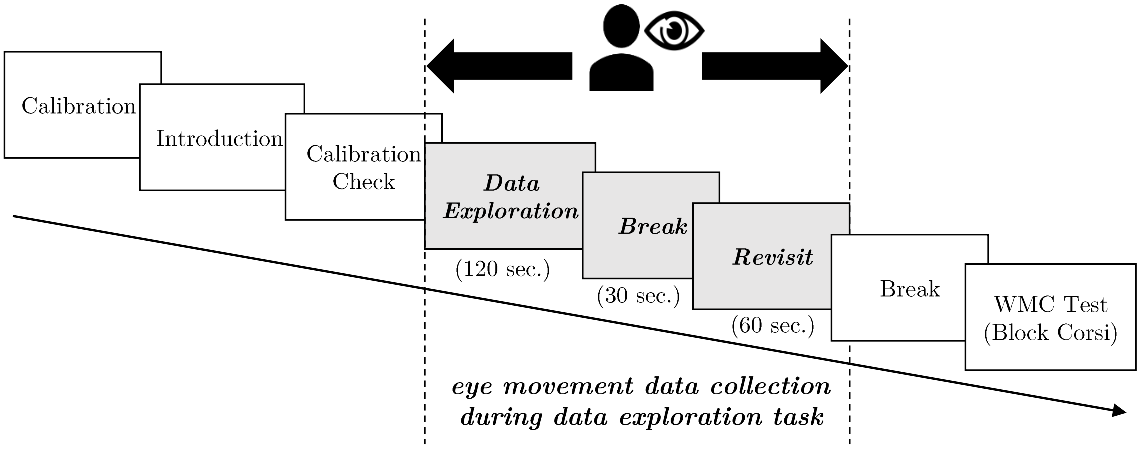


Figure 5.2.: Stages of the designed exploratory experiment to investigate the role of limited attention and working memory.

To better investigate the users' attention and working memory in this experiment, I designed a particular information dashboard that includes six graphs, all with the same complexity regarding their appearance. At the same time, each is considered as an AOI. Figure 5.3 shows the AOIs as well as other sections in the dashboard for this study.

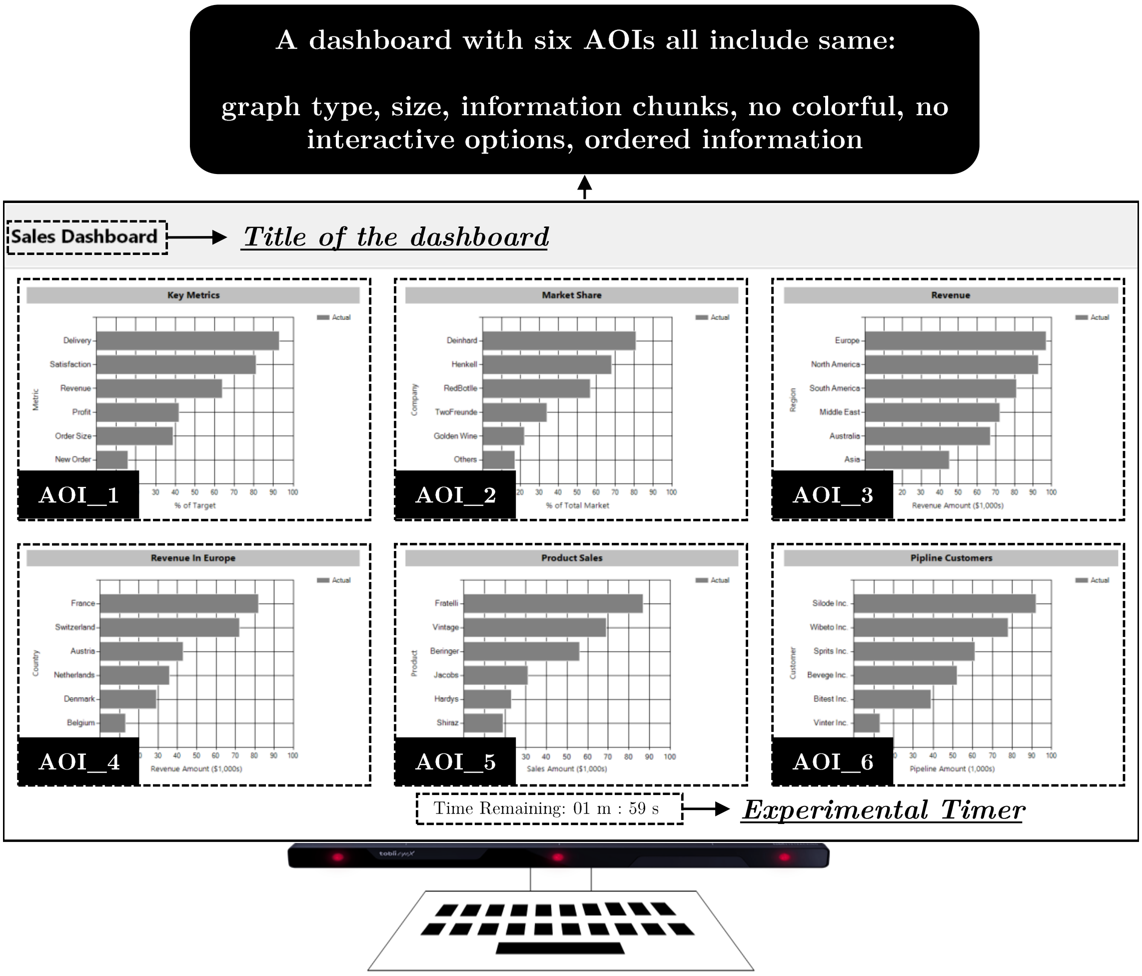


Figure 5.3.: The six pre-defined AOIs based on their position.

I acknowledge that this dashboard does not represent a real-world case, but it is explicitly designed for the experiment to enable isolating the effects of attentional guidance elements such as color, size, order, and shape. The idea is to control their effect on users' sensory memory and focus on goal-driven attention rather than stimulus-driven. Moreover, having a dashboard with equally complex elements empowers determining if the attentional resources are distributed appropriately since they need to allocate the same amount of attention on all graphs. Therefore, the six AOIs have the same type (bar chart) to minimize potential distractions of the users' attention allocation by the applied visualized format (Kelton et al., 2010). Each chart includes six chunks of information as a well-designed visualization promotes chunking (Patterson et al., 2014). I chose six chunks as 7 (plus or minus two) chunks of information is known as the magic number for individuals' WMC (Miller, 1956). To control the effect of attracting attention by the interactive options, the dashboard only includes static charts (Zhicheng Liu and Stasko, 2010) and they are ordered in the same way (high to low value). In addition, the same grey color is used in each AOI to control for color effects (Bera, 2016). With the same visualization format, the number of chunks, color, and the order in all six AOIs, I argue that AOIs in this dashboard have the same complexity. Therefore an appropriate attention allocation while conducting data exploration task should be close to an equal distribution among six charts. As discussed in Chapter 2, Section 2.2.1, this dashboard layout supports controlling stimulus-driven attention and focuses on the user's goal-directed attention. Furthermore, I focus on the overt attention of the users by tracking their eye movement data.

5.1.1.2. Experiment Participants

In total 26 university students (8 female, 18 male) with an average age of 25.11 years participated in this experiment. The original number of participants was 29, but three participants were excluded from the dataset after the study. Two because the recorded eye movement data was available for less than 75 percent of the experiment's actual time, which means less than 90 seconds in the first phase and 45 seconds in the second phase. I assume that this was either an issue with the eye tracker or the participants did not do the task properly by allocating enough attention to the information dashboard. Moreover, one user was removed because of an error and missing results of the visuospatial WMC test.

To group the users based on their WMC, I investigated the collected information by visuospatial Corsi Block-Tapping test (Kessels et al., 2000). This test measures the Corsi Span, which is defined as the longest sequence a user can correctly remember. The higher the number of the Corsi Span, the higher the visuospatial WMC. Scholars have noted that working memory span tasks are the most proper way to compare the individual's WMC with each other (Conway et al., 2005). After running the computer version of this experiment with the help of the PEBL test battery (Mueller and Piper, 2014), the participants were divided into a low and high WMC groups following previously suggested categorization by Lerch and Harter (2001). For that, I performed a median split on visuospatial WMC. The median for the Corsi Span of the participants was 5.75, and I assigned the users with lower values to the *low* WMC group while users with a higher value than 5.75 were assigned to the *high* WMC group. After splitting, the users were equally distributed, with 13 participants in the high WMC and 13 in the low WMC group.

Regarding the sample size, it has been seen that to uncover usability issues, a formative study with eye tracking technology focusing on problem identification, requires fewer participants than a study without eye tracking (Bojko, 2013, p.163). Moreover, in HCI field, one of the main domains of eye tracking studies, a meta-study of 465 publication of the Conference on Human Factors in Computing Systems from 2014, unveiled that the mean sample size for using this method in in-person studies is 21 participants (Caine, 2016). This eye tracking study counts as an exploratory study to investigate users' visual behavior with high and low WMC on information dashboards rather than a confirmatory study. Therefore, I argue that the sample size of 2×13 is sufficient for the goal of this study, which is deriving MRs to design user-adaptive information dashboards in the future.

5.1.1.3. Measurements

Figure 5.4 shows the measurements used in this exploratory study using eye movement data. As can be seen, I mainly focused on three phases of the experiment includes the first visit phase, revisit and end of the task. Furthermore, I focused on three measurements in these phases includes **Attentional Resource Allocation (ARA)** that is measured in all three phases, **Attentional Resource Management (ARM)** that is measured in the first and end of the task and **Resumption Success Rate (RSR)** that is measure in the revisit phase.

ARA: I focused on the distribution of the attention on the six AOIs. These AOIs were named based on their position on the information dashboard, which can be seen in Figure 5.3. I measured the ARA performance of the user on each AOI as this measure is also used in previous eye tracking studies in the IS community (Cheung et al., 2017). Dwell time on each AOIs shows the total time that a user gazed at that AOI through the data exploration phases. Based on the eye-mind assumption, I used the total dwell-time of an AOI to measure ARA (Just and Carpenter, 1980). As an example: a dwell-time of 27 seconds on AOI-3 (Top-Right) provides the total amount of time that this user spent on this AOI in the first phase. I mainly measured ARA of the users in three points of time. First, in the first visit phase, second in the revisit phase, and their end of the data exploration task (first and revisit phase together).

Furthermore, I specifically focused on users' revisit behavior in the second phase of the data exploration task. The revisit phase serves to improve Attentional Resource Management (ARM). The ideal revisit strategy is to increase ARA on the previously low-visited AOIs while decreasing attention on previously high-visited AOIs. Therefore, for proper improvement, the participants need to remember their ARA in the first phase. To measure their ARA in the first phase, I grouped AOIs based on their dwell-time into *"previously low-visited"* AOIs and *"previously high-visited"* AOIs. For each group, I identified the three highest and lowest visited AOIs. Then, I measured the ARA of the users based on these two groups in the revisit phase. The results indicate how users can remember their previous visual behavior.

ARM: As the complexity of all six AOIs is considered to be the same, a more even distribution of dwell-time on all six AOIs is regarded as a better ARM. Therefore, I calculated the variance between the six dwell-times. A lower variance value among the dwell-time values indicates a better ARM. I calculated the ARA and ARM for the first phase of the data exploration task in addition to the end of the task.

RSR: Additionally, I investigated the users' task resumption strategy and the success rate. I explore this at the starting point by identifying the first selected AOI in the revisit phase and compared it with the last visited AOI of the first phase. Based on that, I found the Resumption Success Rate (RSR) for each group of participants separately. This value shows the percentage of users that could select the last AOI before interruption as the first AOI after the resumption.

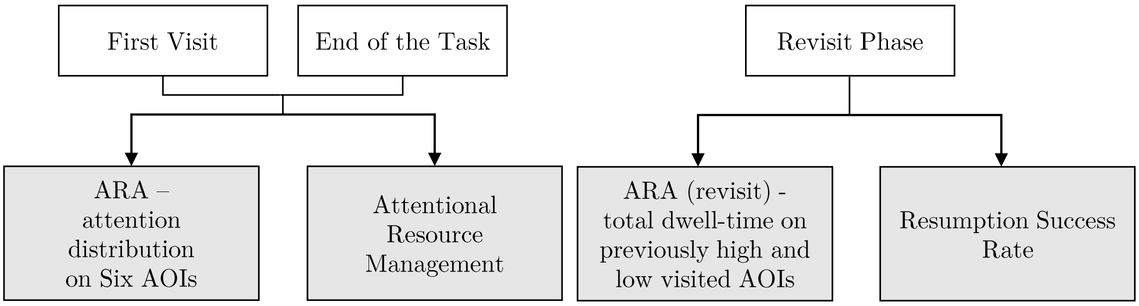


Figure 5.4.: Measures used in the exploratory study.

5.1.2. Data Analysis and Results

5.1.2.1. First Visit Phase

To compare the ARA between the six AOIs in the first phase, I conducted one-way repeated measures Analysis of Variance (ANOVA) for each group separately. Furthermore, the heatmaps for both groups in the first visit phase can be seen in Appendix B Figure B.3.

For users with high WMC, Mauchly's test indicated that the assumption of sphericity was not violated. The results revealed no significant difference in the dwell-time between the six AOIs for users with high WMC ($F(5, 60)=1.99$, $p=0.093$). This result highlights that users with high WMC distributed their ARA properly. However, the same test for users with low WMC shows that there was a significant difference ($F(5, 60)=2.73$, $p=0.027$) in ARA. It shows that dwell-times are different among AOIs. In the next step, a post hoc comparison using the Tukey test was carried out. There was a significant difference between the dwell-time on AOI-1 and AOI-3 ($p=0.023$) and AOI-1 and AOI-6 ($p=0.036$). The users had, on average, around six seconds less dwell-time on AOI-3 and 5 seconds less in AOI-6 in comparison with AOI-1. Figure 5.5 displays the results of the ARA in the first phase for users with high WMC and low WMC. It shows that the ARA for both groups follows almost the same pattern while they allocated less time to AOI-3 (down-left) and AOI-4 (down-middle) than to the other AOIs.

Figure 5.6 shows the ARM of the users as the variance between the six dwell-times for the first visit phase. After checking the normality distribution of the data, an independent t-test was conducted to compare the ARM. The results show that there was not a significant effect between users with high WMC ($M=19.69$, $SD=11.71$) and low WMC ($M=29.54$, $SD=17.41$), $t(21)=-1.647$, $p=0.11$). Therefore, it confirms that both groups had the same performance in managing attention in the first phase. The lower mean values of ARM indicate that the dwell-times tend to be very close to each other, and the users could properly distribute their attention.

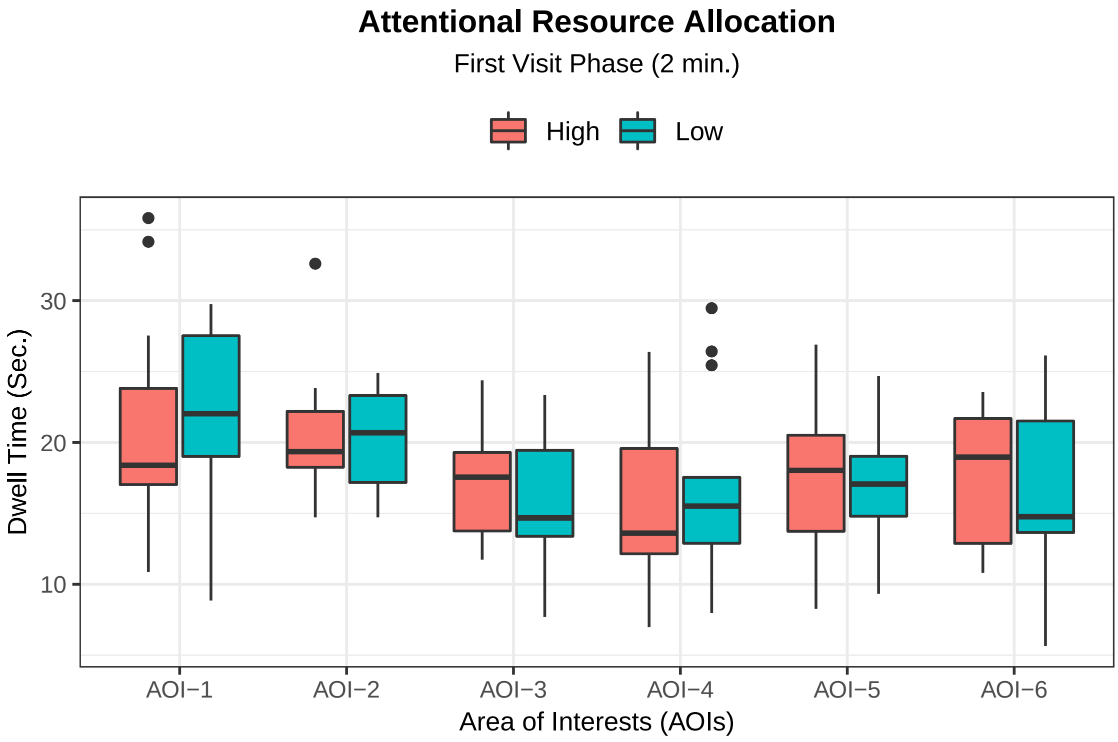


Figure 5.5.: Distribution of dwell-times on six AOIs after the first phase of the experiment.

Figure 5.6.: The ARM of participants after the first phase of the task.

5.1.2.2. Revisit Phase

Figure 5.7 shows the ARA on each group for users with high WMC (left) and low WMC (right). Furthermore, the heatmaps for both groups in the revisit phase can be seen in Appendix B Figure B.3. The revisit step is considered as an opportunity to improve the management of limited attentional resources. In this step, I investigated the users' ARA in two groups of AOIs: *"previously high-visited"* and *"previously low-visited"* AOIs. The selection of AOIs for each of these groups was discussed in the previous section.

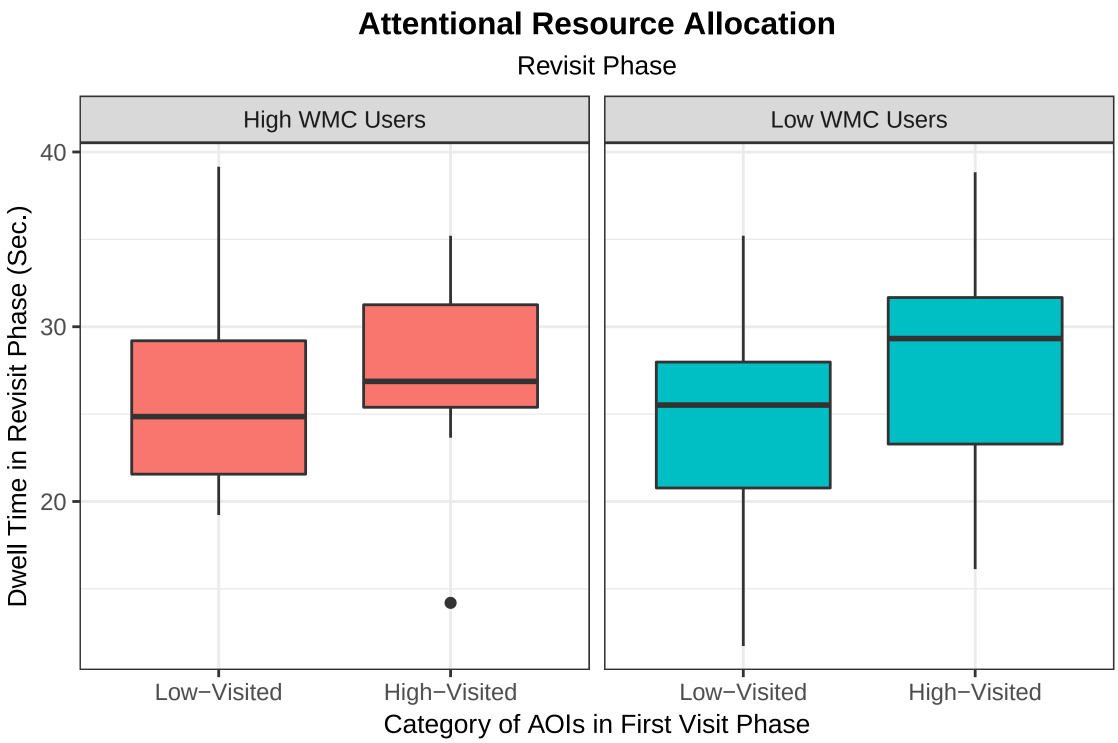


Figure 5.7.: Total dwell-times on previously low and high visited AOI in the revisit phase for users with high WMC (left). Total dwell-times on previously low and high visited AOIs in the revisit phase for users with low WMC (right).

To compare the ARA of previously high-visited and low-visited AOIs for users with low WMC, I conducted paired-sample t-test. The results show that there is not a significant effect between dwell-time on previously high-visited AOIs (M=27.08, SD=6.78) and previously low-visited AOIs (M=24.34, SD=6.41), t(12)=-0.96, p=0.35). Furthermore, the results from the paired-sample t-test for users with high WMC show that there is no significant difference in previously low and high visited AOIs for these users t(12)=-0.34, p=0.73. The mean for scores of previously low-visited AOI was 26.13 (SD=5.87), while the mean of previously high-visited AOIs was 27.12 (SD=5.12). Moreover, running independent tests for comparing the results of previously low and previously high-visited AOIs does not highlight any difference between both groups with (t(23.81)= 0.73, p=0.46) for previously low-visited AOIs and (t(22.33)=-0.28, p=0.77) for previously high-visited AOIs. As can be seen in Figure 5.7, both groups repeated their visual behavior of the first phase in the revisit phase and have higher dwell-time on AOIs with previously high values. In fact, they could not distinguish between previously low and high visited AOIs in their revisit patterns. I can conclude that both groups had difficulties remembering their previous ARA and improving it. These results show that having higher WMC does not necessarily support having a better strategy in the revisit phase.

Furthermore, Figure 5.8 indicates the last selected AOIs by users in the first phase and the first selected AOIs at the beginning of the revisit phase. As can be seen, in the first phase, AOI-6 is selected more often as the last AOI than others, while other AOIs also were selected as the last AOIs by some other users. However, in the revisit phase, the first selected AOIs are AOI-1 and AOI-2 that are selected by 85% of the users and have the highest density. This shows that most users had difficulty resuming their data exploration after the break and decided to start the data exploration task from the AOIs that they already allocated attention more in comparison with the others. Therefore the RSR is low for the users in both groups. This highlights the difficulty of resuming the task after an interruption (Addas and Pinsonneault, 2015) also while exploring visualized information on dashboards. Overall, difficulties in remembering last visited AOI results in task resumption failures (Bailey and Konstan, 2006). Furthermore, starting the revisit phase from the top-left or top-middle, while these two AOIs have almost always the highest dwell-time in the first phase for both groups, indicates the lack of a proper strategy to improve ARM in the revisit phase. The results of dwell-time on previously low and high-visited AOIs in addition to these results, highlight that the users from both groups did not use the revisit phase as an opportunity to improve their information processing and repeated their information processing similar to the first phase.

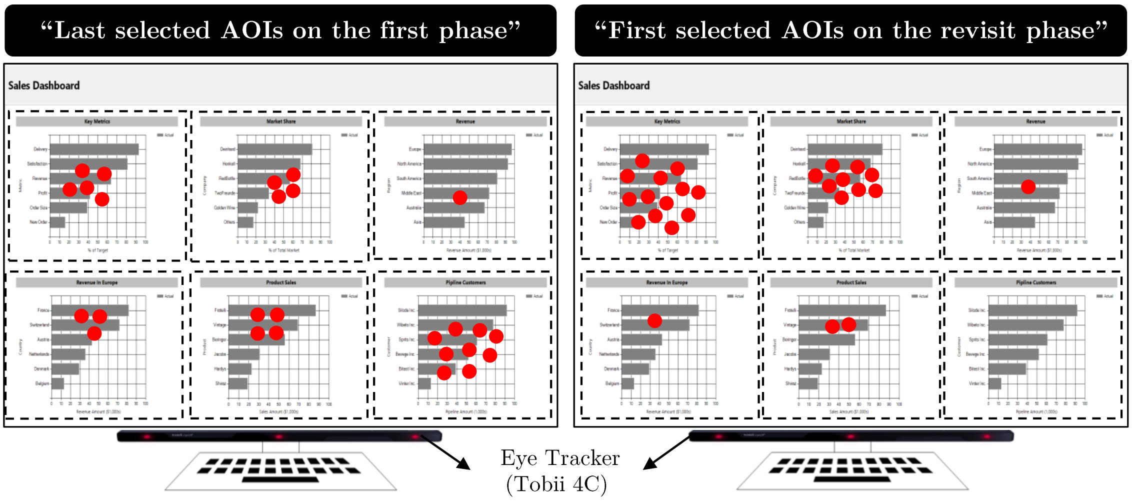


Figure 5.8.: Comparing last selected AOI in the first phase with first selected AOI in revisit phase of the data exploration task.

5.1.2.3. End of the Task

In this section, I investigate the overall ARA after finishing the data exploration task (after finishing the first phase and revisit phase). The analysis follows the same approach as the first phase by investigating the ARA and ARM of the users. Figure 5.9 shows the dwell-time on each AOIs for users with high and low WMC after finishing the task. Furthermore, the heatmaps for both groups at the end of the task can be seen in Appendix

B Figure B.3. To compare the dwell-time on the six AOIs, I conducted a repeated measure one-way ANOVA. The Mauchly's test indicated that the assumption of sphericity was not violated and the results revealed a significant difference in dwell-times between the six AOIs for both groups of users with high WMC (F(5, 60)=5.149, p=0.000) and users with low WMC (F(5, 60)=5.338, p=0.000). Therefore, the ARA is not distributed well among the six AOIs after finishing the task, and users allocated more attention to some of them. Comparing the two groups reveals that users of both groups allocate more attention to the top left and middle charts (AOI-1 and AOI-2) than to other charts.

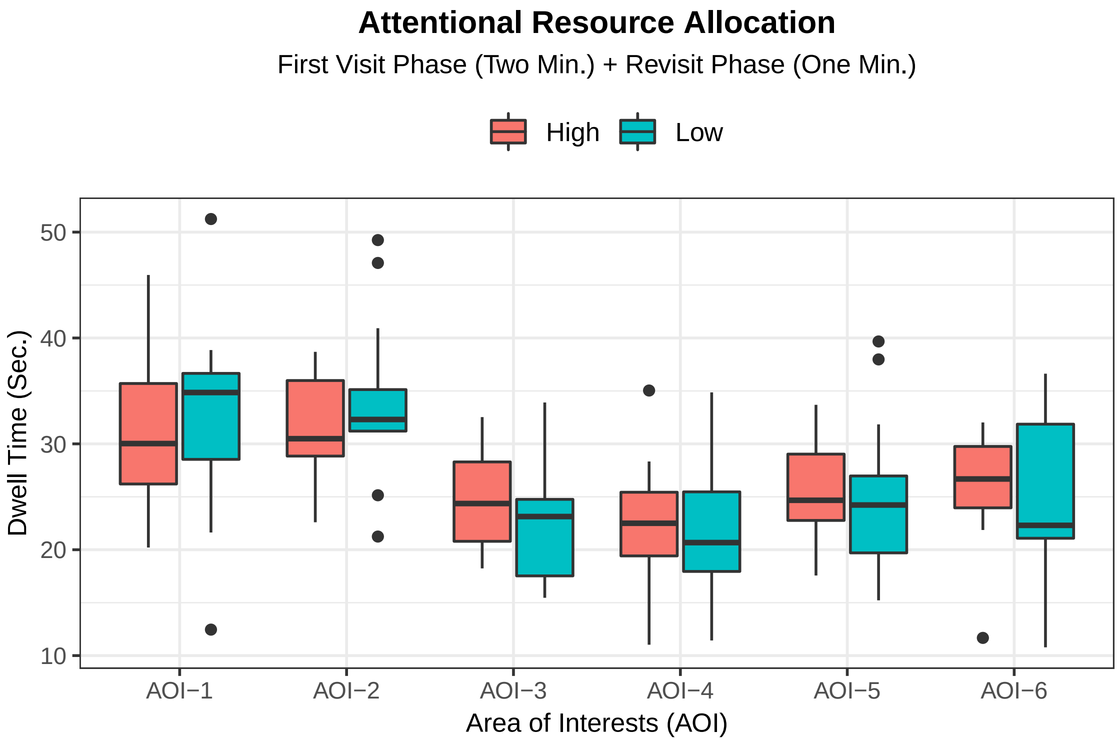


Figure 5.9.: Distribution of dwell-times on six AOIs at the end of the task.

To test for a difference of allocated attention to AOIs, I conducted post hoc comparisons using the Tukey test for each group separately. Table 5.1 represents the results of this test in both groups. For the users with high WMC there was a significant difference between the dwell-time in five conditions, with three of them being relevant to AOI-1 and two of them to AOI-2 (Top-middle). As can be seen in Figure 5.9, the users with high WMC allocated more attention to the charts on the top left, and middle positions than on top right and down left positions. The differences are between AOI-1 and AOI-3 (p=0.039), AOI-1 and AOI-4 with a highly significant difference (p=0.000) and a weak significant result between AOI-1 and AOI-5 (p=0.046). Moreover, AOI-2 and AOI-4 with a highly significant difference (p=0.000) and AOI-2 and AOI-3 with a weak significance (p=0.036). Also, the post hoc results for users with low WMC reveals six differences in the conditions. Two of these conditions are relevant to AOI-1 (top-left), while the other four are relevant to AOI-2 (top-middle). AOI-1 is different from AOI-3 (p=0.003) and AOI-4 (p=0.005). Furthermore, the ARA is highly different between AOI-2 and AOI-3 (p=0.000), AOI-4 (p=0.000) while lower significant for AOI-5 (p=0.017) and AOI-6 (p=0.009). These

	Users with High WMC		Users with Low WMC	
Conditions	diff	p	diff	p
AOI-1 / AOI-2	-0.389	1.000	1.797	0.988
AOI-1 / AOI-3	-6.725	0.021 *	-10.290	0.003 **
AOI-1 / AOI-4	-9.671	0.000 ***	-9.981	0.005 **
AOI-1 / AOI-5	-6.156	0.046 *	-7.207	0.106
AOI-1 / AOI-6	-5.740	0.078	-7.662	0.070
AOI-2 / AOI-3	-6.336	0.036 *	-12.087	0.000 ***
AOI-2 / AOI-4	-9.282	0.000 ***	-11.779	0.000 ***
AOI-2 / AOI-5	-5.767	0.076	-9.004	0.017 *
AOI-2 / AOI-6	-5.351	0.123	-9.459	0.009 **
AOI-3 / AOI-4	-2.946	0.741	0.308	1.000
AOI-3 / AOI-5	0.569	0.999	3.083	0.882
AOI-3 / AOI-6	0.985	0.997	2.628	0.937
AOI-4 / AOI-5	3.515	0.569	2.774	0.922
AOI-4 / AOI-6	3.931	0.441	2.319	0.963
AOI-5 / AOI-6	0.415	1.000	-0.455	0.999
Note: * $p < 0.05$, ** $p < 0.01$, *** $p<0.001$				

Table 5.1.: The results from Turkey test by comparing the dwell-times of participants on six AOIs after finishing the data exploration task.

results highlight that users with low WMC are mostly focused on AOI-2, and this AOI has a significant difference compared to all other AOIs except AOI-1.

As I controlled for elements that affect ARA of the users, such as color, size, motion, and importance level in the dashboard's design (discussed in Section 5.1.1.1), I can argue that the position of charts in the information dashboard is the main reason for unbalanced ARA. It can be seen that users allocate the attention differently on the elements which are positioned top left and top middle than the other locations. Comparing the ARA in the first and after the revisit phase, I can conclude that the revisit phase did not help users with low WMC improve their ARA. Although users with high WMC had a proper allocation in the first phase, they changed their behavior and focused on some of the AOIs more than on others.

In the next step, I compared the ARM of the users of both groups at the end of the task. Figure 5.10 shows ARM of the users at the end of the experiment. Furthermore, the heatmaps for both groups at the end of the task can be seen in Appendix B Figure B.3 and shows how the ARM of the users was in the end. The results from the independent wilcox test showed that there was a highly significant difference between the variance of dwell-times of users with high and low WMC ($W=34$, $p=0.008$). The mean of users with high WMC was 40.33 ($SD=29.28$), while the mean of users with low WMC was 72.59 ($SD=37.90$). This shows that users with low WMC have more challenges to manage their attention than high WMC users. In comparison to the ARM in the first phase, the mean value for the performance of low WMC changed from $M=29.54$ ($SD=17.41$) in the first phase to $M=72.59$ ($SD=37.90$) after finishing the second phase. Whereas for users with high WMC, this change was from M=19.69 (SD=11.71) to M=40.33 (SD=29.28). This indicates that the revisit strategy does not support any of those groups to improve their ARM. Nevertheless, the overall ARM was worse for users with low WMC compared to users with high WMC.

Figure 5.10.: The ARM of participants at the end of the task.

5.1.3. Derived Meta-requirements

The results from the previous section highlight difficulties of users while exploring dashboards. Based on these results, the theoretical foundation discussed in Chapter 2, Section 2.2 and existing attention and visual memory challenges of users in the information visualization (Healey and Enns, 2012), I extracted six MRs for designing innovative dashboards that consider users limitations in data exploration task. Table 5.2 shows the list of identified MRs. There are three MRs that focus on system adaptation without involving users. These types of MRs concentrate on collecting data about users and make the dashboard more intelligent. The second focus is user adaptation, in which three MRs focus on increasing the user's awareness about their problem by providing feedback and let them improve allocating attentional resources. These two categories are also aligned with the identified focus for eye-based IIS that discussed in the Study I of this thesis.

As the first MR **(MR1)**, I argue that there is a need to recognize users' visuospatial WMC and adopt the dashboard's design based on that. This is known as an important individual characteristic in processing visualized information (Healey and Enns, 2012; Toker et al., 2013), and also previous studies have shown that personalized features affect the information processing and attention of the users (Tam and Ho, 2006). Moreover, this study shows that the chart's position affects the ARA of the users similar to the findings from other studies that investigated other UI types (Lorigo et al., 2008; Nielsen, 2006). Also, the total number of available information significantly influence the pattern of attention decay (Ahn et al., 2018). In the designed dashboard, the top-left and the middle-top position were visited more than other locations for both groups. Furthermore, the results show that users with low WMC are allocating significantly more attention to the middle-top position than to different positions. At the same time, this is not the case for users with high WMC. Therefore, as the second MR **(MR2)**, I argue that a user-adaptive information dashboard should adopt the position of charts based on their level of importance. As an example, the charts with vital information should be positioned on the left-top or top-middle. Moreover, as the third MR **(MR3)**, I argue that the position of important charts should be considered slightly different for users with high and low WMC.

The results of the ARA indicate low performance for both groups. Moreover, in the revisit phase, they had the chance to improve their ARA by visiting the previously low-visited AOIs and ignoring high-visited AOIs. However, but both groups failed to select a proper revisit strategy. Therefore, as the fourth MR **(MR4)**, I argue that there is a need to support ARA of users while exploring dashboards. Providing attention feedback is suggested by researchers to support this need (Göbel and Kiefer, 2019; Otto et al., 2018; Qvarfordt et al., 2010). Also, comparing the last selected AOI in the first phase and first selected AOI in the revisit phase uncovered that the users of both groups have difficulties in resuming their data exploration and repeated it from the beginning. Previous studies have shown that this happens when users have difficulty in remembering which activities have been completed (Singh, 1998). Therefore, as the fifth MR **(MR5)**, I argue that there is a need to guide users in selecting a proper revisit strategy that supports them to resume their task in the case of an interruption. Previous studies have shown that providing support for resuming an interrupted tasks with visualization of users eye movement data helps users to have lower resumption lag and improve their performance (Jo et al., 2015; Kern et al., 2010). Also, the results of the ARM are different for users with high and low WMC. It shows that users with low WMC have a significantly lower performance in managing their attention than users with high WMC. As the sixth MR **(MR6)**, I argue that this attention feedback should be individualized and adapted to the users' WMC.

Focus	#	Meta Requirements
System Adaptation	**MR1**	Information dashboards should be able to adopt their design based on the visuospatial WMC of their users to support data exploration task.
	MR2	Information dashboards should be able to adopt the position of charts based on their level of importance in order to be more visible for users.
	MR3	Positioning important charts should be a bit different for users with high and low visuospatial WMC.
User Adaptation	**MR4**	The information dashboard should support users with high and low visuospatial WMC to control their limited attentional resources by providing attention feedback while exploring information dashboards.
	MR5	The information dashboard should be able to support users to select a proper revisit strategy that helps resuming the interrupted task.
	MR6	The attention feedback should be individualized and adapted to the users visuospatial WMC.

Table 5.2.: MRs for designing innovative information dashboards that consider limited attentional resources and working memory.

5.1.4. Summary

As Study I in the first part of the first design cycle, I conducted an exploratory eye tracking study to identify users' attention problems with high and low WMC while exploring information dashboards. Eye tracking technology is used to assess the impact of information dashboard on users' information processing capacity as suggested by IS researchers (Dimoka et al., 2012). Although a single visualized information can support users to have a better overview of the data, several of them on one page can challenge the limited cognitive ability of the users again. Nevertheless, there is a lack of knowledge in the cognitive status of users while using information dashboards (Niu et al., 2013; Yigitbasioglu and Velcu, 2012). Designing effective dashboards requires a detailed understanding of the underlying cognitive processes of their users (Lerch and Harter, 2001). Therefore, as Study II, I investigated the visual behavior of information dashboard users with eye tracking technology. Specifically, I focused on the role of limited attentional resources and visuospatial WMC as two important individual characteristics and checked how these elements affect data exploration tasks on dashboards.

This study contributes to the information dashboard design research by identifying six MRs that should be considered when designing dashboards. As a practical contribution, these findings support dashboard designers to better understand the role of limited attention and working memory and design more effective dashboards by especially considering the visuospatial WMC of their user and their attention allocation strategy. Also, these MRs can be used by researchers in DSR to define DPs, suggest new features, and investigate the effect of them (Gregor and Hevner, 2013). Both groups of MRs offered in this study are suggested by researchers to investigate for future BI&A systems integrating eye tracking technology (Silva et al., 2019). Generally, there are only a few attentive IS applications focusing on system adaptation with eye tracking technology (e.g., (Maglio et al., 2000) focused on system adaptation). Also, there is a lack of usage on eye tracking technology for increasing user-awareness while working with IS applications (Lux et al., 2018). The results from Study I shows the increasing interest of the community on providing feedback based on users' eye movement data that increase support them to track themselves and increase their self-awareness. However, there is a lack of evidence on using integrating self-tracking such techniques in the workplaces (Rivera-Pelayo et al., 2017). Therefore in this thesis, I mainly focus on the user adaptation category of the MRs (MR4, MR5, MR6) to integrate in the next steps of the DSR project. These MRs are covered by providing attentive information dashboards with individualized VAF for data exploration and resuming interrupted tasks.

5.2. Study III: Overview

The results from the Study II show that users have difficulty allocating their limited attentional resources while exploring information. Attention is a limited resource of humans (Chun et al., 2011), and the huge amount of information can create a poverty of attention (Simon, 1971). When using information dashboards in a data exploration task, a proper allocation of attentional resources is essential for the decision-maker to avoid missing important information. Thus, there is a need to manage attention during dashboard exploration. Also, users need to scan complex displays systematically to extract relevant information (Proctor and Vu, 2006). Missing important information, maybe the consequences of high attentional demand or an inappropriate attention allocation (Roda, 2011). Based on the provided list of MRs, I focus on increasing users' awareness perspectives to provide suggestions. Especially in this study, I focus on providing suggestions for the **MR4**, which is the need to provide VAF to support users.

In the digital environment, researchers have called for designing AUI and specifically attention management support features that preserve users from such attentional breakdowns (Bulling, 2016; Roda and Thomas, 2006; Vertegaal, 2003). The details for AUIs are discussed in Chapter 2, Section 2.3.2. Eye trackers are known as the main tool for designing such systems (Bulling, 2016; Majaranta and Bulling, 2014). Based on the eye-mind assumption, where users are fixating is underlying their cognitive process, such as dedicating their attentional resource (Just and Carpenter, 1980) and users mostly explore dashboards through their eyes. The attentional allocation is the set of processes enabling and guiding the selection of incoming perceptual information (Eriksen and Yeh, 1985). AUIs that provide VAF is known as being supportive of recovering from attentional breakdowns and improving performance in several contexts (D'Mello et al., 2012; Otto et al., 2018; Sarter, 2000; Sharma et al., 2016). Study I provides a list of studies that focus on increasing user's awareness by providing VAF. Also, the research gap for integrating such support is already discussed in Chapter 1, Section 1.2. I focus on closing this gap and address the third RQ in this study:

> ***RQ3:*** *What type of VAF enhances users' ability to manage attentional resources while exploring information dashboards?*

As Figure 5.11 shows, this study focuses on the remaining steps in the first design cycle. In this study, I first propose MRs to design attentive information dashboards with VAF and then investigate the effects of two common approaches for designing VAF using eye movement data (off-line usage of eye movement data Vs. real-time usage of eye movement data). For that, I suggested three different VAF types, two based on off-line records and one based on real-time tracking of user's eye movement data. Later, I evaluated the effects of these three VAF types on users' ability to manage limited attentional resources in an eye tracking pilot study and presented the results.

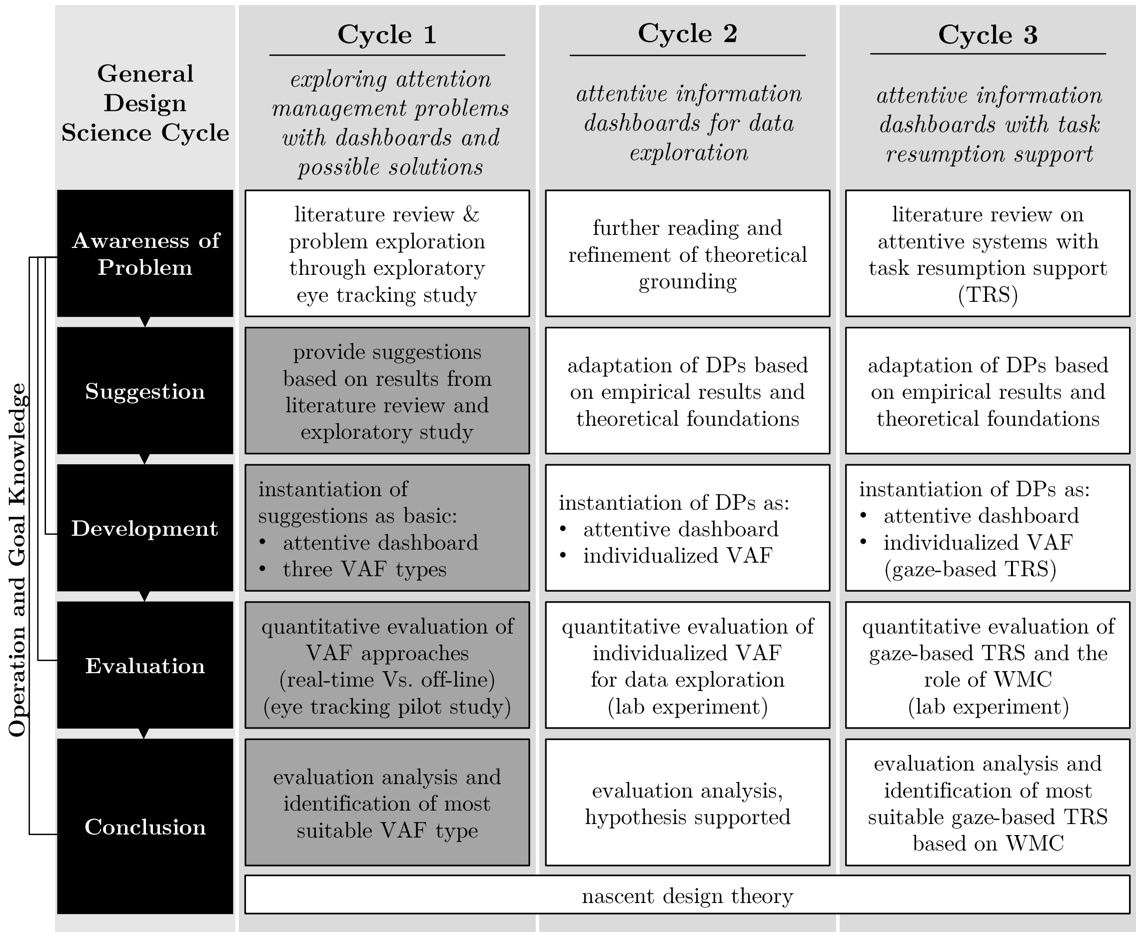


Figure 5.11.: The focus of Study III in this DSR project.

5.2.1. Meta-requirements

As the first part, I discuss the initial MRs for designing an information dashboard sensitive to the users' attention. I mainly focus on providing support for data exploration tasks as **MR4** derived in the previous study.

Information dashboards and the included interactive technologies have the potential to bias decisions by focusing attention on a limited set of alternatives, increasing the salience of less diagnostic information, and encouraging inappropriate comparisons (Alberts, 2017; Dilla et al., 2010). What users see or do not see depends on how they allocate their attention while interacting with BI&A dashboards. Missing important information on BI&A dashboards can be explained by phenomena such as inattention blindness (Mack and Rock, 1998) or change blindness (Simons and Rensink, 2005), which has the root in inappropriate attention allocation. Having a comprehensive overview of the presented information on BI&A dashboards and also notice changes from the past are essential for the decision-makers. Therefore, I argue that attentive information dashboards should be able to capture the users' current visual attention. Thus, I propose the first MR (MR1) as the need to monitor the users' visual attention.

There exist subjective as well as objective measurements for the users' visual attention.

Researchers argue that the users' eye movements and their current eye fixations are the approximation for their visual attention and cognitive processes (Hayhoe and Ballard, 2005; Kowler, 2011; Liversedge and Findlay, 2000; Rayner, 1998). Eye tracking technology can be used to detect the users' gaze position and collect the relevant eye movement data (such as dwell-time, fixation and saccade) in real-time (Duchowski, 2002). Based on this data, the users' visual attention can be extracted and use as an input for designing innovative systems (Bulling and Gellersen, 2010; Bulling et al., 2011). Thus, I propose the second MR **(MR2)** as the need for integrating eye tracking technology to collect users' eye movement data.

Decision-makers face the challenge of making biased decisions by focusing their attention on a limited set of alternatives on BI&A dashboards (Alberts, 2017; Browne and Parsons, 2012; Dilla et al., 2010). Having only a subset of the required information can result in inaccurate decision making. Providing feedback on their current visual attention can enable them to allocate their visual attention more efficiently and avoid attentional breakdowns and miss important information. Feedback refers to sending back information about what action has been done, and various kinds of feedback are available for interaction design (Preece et al., 2015). As discussed in the results of the Study I, how and where users paid attention is known as a valuable source of information to provide corrective feedback. Such feedback can increase users' awareness and direct users to allocate attention to missed important information while exploring the dashboard. Moreover, having efficient attention allocation on the dashboard supports decision-makers to compare the results and find the changes. Thus, I propose the third MR **(MR3)** as the need for providing feedback on the users' visual attention.

With these initial MRs for designing attentive information dashboards that provide VAF for data exploration tasks, I proposed three types of VAF. Two of them work based on off-line records of eye movement data, and one works by tracking users' eyes in real-time. The development of these VAF types is discussed in the next session.

5.2.2. Instantiation of VAF Types

To better understand the effect of each VAF type, I designed two specific information dashboards that increase the internal validity of the experiment. As can be seen in Figure 5.12, these dashboards have a similar layout and used in two phases of the experiment. Similar to Study II, these dashboards are designed in a way that minimizes the influence of external factors on the user's ARA. Therefore, as discussed in Chapter 2, Section 2.2.1, this dashboard layout supports controlling stimulus-driven attention and focuses on the user's goal-directed attention. Furthermore, I focus on the overt attention of the users by tracking their eye movement data. The actual size of this dashboards with the content can be seen in Appendix C in Figures C.1 and C.2. The designed information dashboards consist of six charts while each is considered as an AOI. I tried to design each AOI in a way to have the same complexity by having the same chart format, amount of information chunks, same size, no color, etc. With having the same complexity, I assume that a proper ARA is close to an even distribution of the ARA on all six AOIs. To select an example of a proper and improper ARA, I considered the dwell-time on six AOIs from the users in Study II. For that, I calculated the variance among six dwell-time values for all users. Later, having lower variance shows that ARA was close to the even distribution, and proper and the higher variance shows the improper ARA examples.

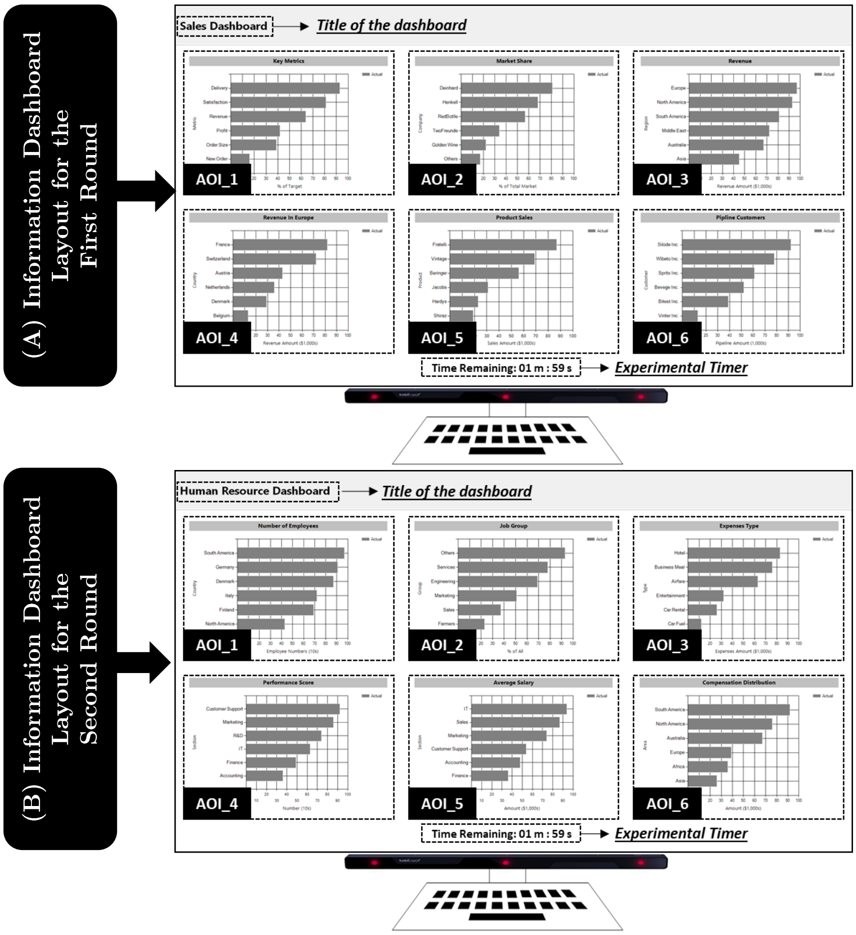


Figure 5.12.: The information dashboard layout used in two rounds of the experiment.

Feedback is known as a constructive element that sends back information about what action has been done while allowing the user to continue with the activity (Preece et al., 2015). Therefore, a proper design of VAF for data exploration tasks on information dashboards should enable users to recognize how their previous ARA was and let them continue their data exploration task. Such support can be either delivered by the usage of off-line records of eye movement data from previous expert users (e.g., (Sridharan et al., 2012)) or by using users' real-time eye movement data (e.g., (Qvarfordt et al., 2010)). Figure 5.13 presents the summary of these three VAF types as suggested for the first design cycle of the DSR project. First, I designed an individualized VAF by considering the user's eye-movement in real-time. This type of VAF displays the actual ARA by presenting the dwell-time on each chart of the dashboard as a time format. I assume that having such information assists users to remember their previous ARA. Consequently, it helps in selecting a suitable data exploration strategy within the revisit phase. The second VAF type is a general VAF that presents an example of improper ARA. The design of this VAF type is equivalent to the individualized VAF, and only the duration values are different in order to provide an example of an improper ARA. Furthermore, the users receive an explanation that informs them that it is an improper example of ARA. The third VAF, is again a general VAF with the same design. In contrast to the second VAF, the values in this VAF type expose an example of a proper ARA. I assume that both second and third VAF types, as general VAF types, give a hint to the participants for recalling their previous ARA from their own memory, consequently, let them plan the revisit phase. The dwell-time values of second and third VAF types are the same for all participants while they changed for the users with an individualized VAF. Moreover, users received a short text on top of each VAF that explains the VAF type. The values of the proper and improper VAF types are coming from the ARA of users with the individualized VAF. I first conducted the study with the users that received an individualized VAF and considered the dwell-time on six AOIs in the first phase of the experiment from these users to find the values for general VAF types. For that, I calculated the variance among the collected six dwell-time values for all participants and selected the ARA with the lowest variance as the proper example of ARA and the highest variance as the improper ARA. Figure C.3 in Appendix C shows the design layout of all VAF types used in this study. Individualized VAF shows the actual ARA of the user and for the general VAF the values in Figure 5.13 are used.

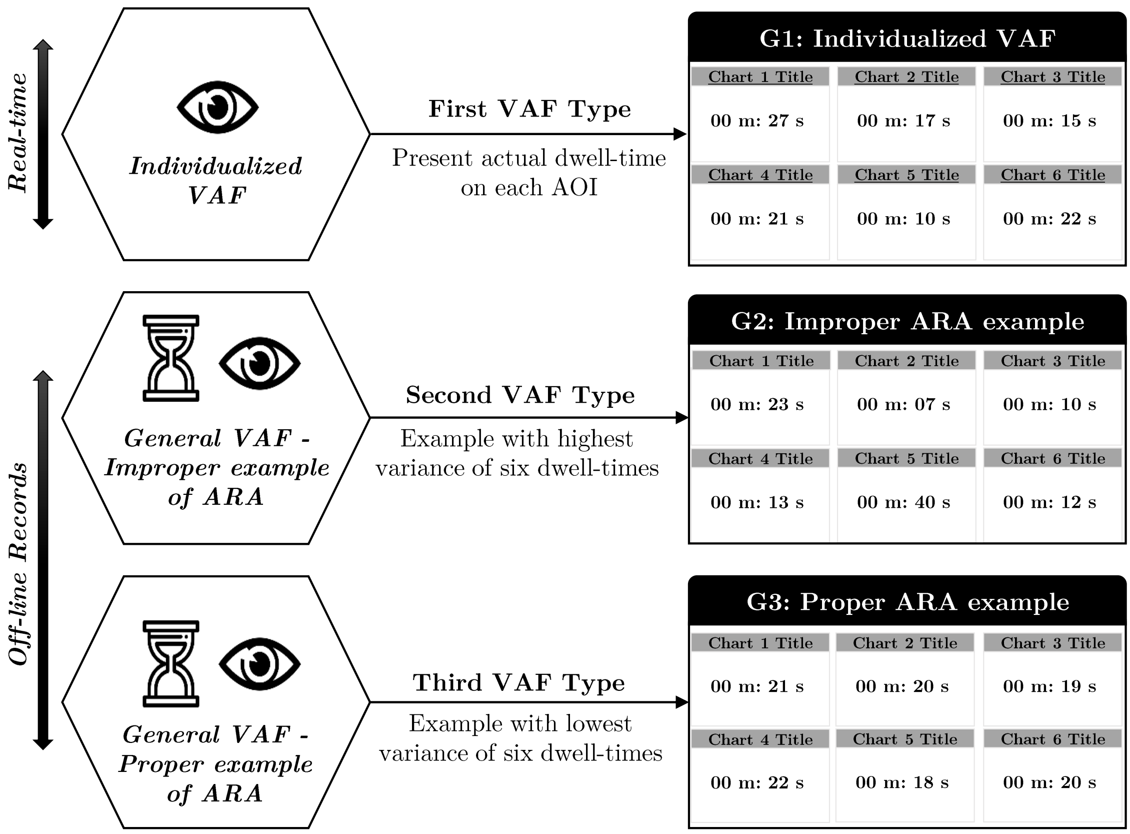


Figure 5.13.: Three VAF types that are suggested and evaluated in Study III.

5.2.3. Eye Tracking Pilot Study

5.2.3.1. Experiment Design

To test the influences of VAF types, I executed an eye tracking experiment in a controlled lab environment. The experimental design was 2 × 3 mixed design in which with or without VAF was manipulated within subjects and VAF types were manipulated between subjects. In this experiment, each subject had to conduct data exploration tasks in two rounds on two different information dashboards, which both had the same design but different content. These dashboard can be seen in Appendix C in Figures C.1 and C.2. For each data exploration task, participants had three minutes to explore the dashboard in total. After two minutes, they were interrupted for 30 seconds and later resumed the task for one more minute. During the first round, the interruption phase counted as a break, and participants were asked to wait for 30 seconds before continuing. During the second round, each participant got one of the three VAF types presented in the previous section.

The experiment procedure started by calibrating the eye tracker for each participant individually with Tobii Eye Tracking Core Software. In the second step, screen-based instructions were given to explain the experimental steps and illustrated the concepts used in the dashboard. These instructions were followed by control questions to ensure the common understanding of concepts on the dashboard. After that, the main part of the experiment started and can be seen in Figure 5.14. First, participants conducted the first round (without VAF) of the experiment in which they explored the dashboard for two minutes (first phase) and then they had a break for 30 seconds. Next, they had the opportunity to resume the data exploration task for one more minute and finish the first round. Then, the calibration status was checked again, and in case of any errors, the system enforced the execution of a recalibration. Also, a rest phase was included for two minutes to control for carryover effects from the first round. Next, the second round (with VAF) of the experiment is started. In this round, users had a data exploration task similar to the first round but this time with a new dashboard. In this round, participants received one of the designed VAF types after two minutes instead of having a break. As time was controlled in each step, the participants got a timer in the footer of the screen that displayed the remaining time in all phases of the experiment. In the end, demographic questions were asked as a survey.

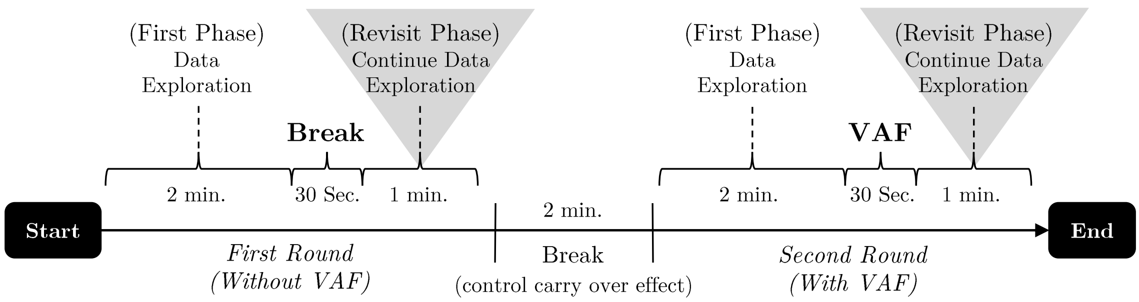


Figure 5.14.: Stages of the designed eye tracking pilot study.

5.2.3.2. Experiment Participants

In total 29 university students (8 female, 21 male) with an average age of 25.03 years (SD=2.32) participated in this experiment. After checking the collected data, I removed two participants since the total collected dwell-time was less than 3/4 of the time assigned to each phase. This can be because these users ignored some part of the task or an error in the calibration. The remaining 27 participants were distributed across three groups (G). 11 participants were assigned to *G1* with the individualized VAF, 8 participants to *G2* with the improper example of ARA (general VAF) and 8 participants to *G3* with the proper example of ARA (general VAF).

5.2.3.3. Measurements

The data analysis is focused on comparing the ARA performance and Attention Shift Rate (ASR) of the participants as the dependent variables in the revisit phase of both rounds (with and without VAF). The revisit phase is considered as an opportunity to improve the ARA by focusing on previously low-visited charts of the first phase. Thus, for each round, I detected the three low-visited charts in the first phase and measured the dwell-time on these charts in the revisit phase. Also, I captured the focused attention and how they engaged in the task by tracking the number of transitions between the AOIs. ASR shows the centering of attention on a limited stimulus field (Ishii et al., 2013). Here, having a lower number of transitions is considered as having higher focused attention. Figure 5.15 shows the visual representation of measurements considered in this study with and example values.

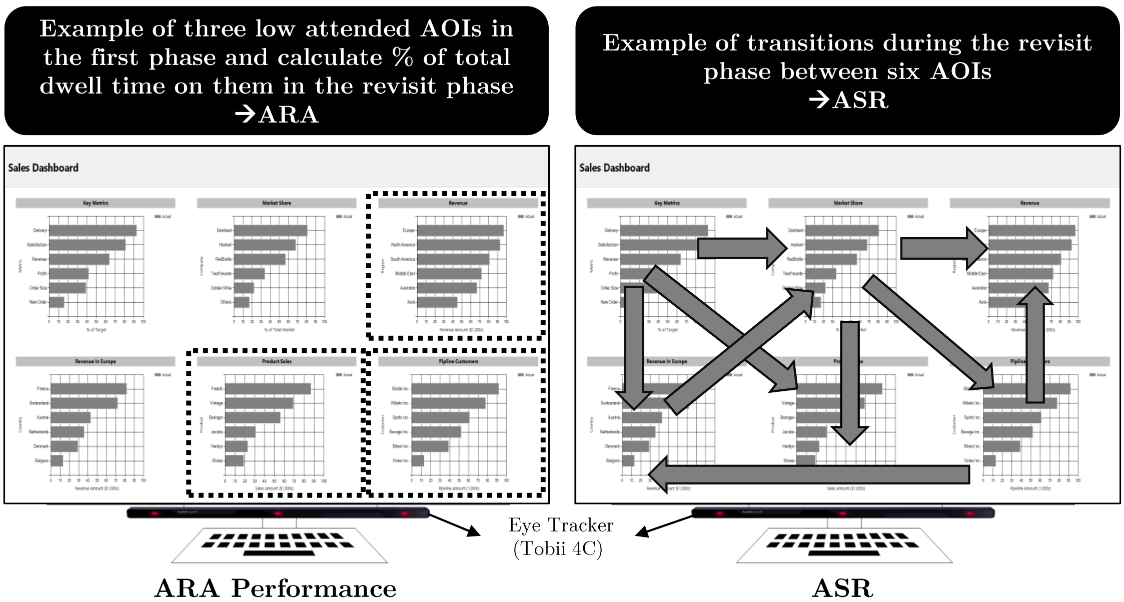


Figure 5.15.: Measures used to compare three suggested VAF types.

5.2.4. Data Analysis and Results

To test the difference between groups in these two rounds, I conducted a mixed design ANOVA test with groups as between subject and the dependent variables as within subject. I did this test for each dependent variable separately and the results did not show any significant difference among the three groups for both dependent variables. I assume that these results occurred because of the low sample size in this eye tracking pilot study. To investigate the effects of VAF types in more detail, I performed a within-subject analysis for each group separately by conducting a paired-sample t-test. Figure 5.16 shows the ARA for each group. Furthermore, the heatmaps based on collected eye movement data for three groups can be seen in the first visit, and the revisit phase for each round of the experiment can be seen in Appendix C and Figures C.4 and C.5.

For the group with an individualized VAF (G1), the results confirm that there was a significant difference in the ARA performance of the first (M=45.69, SD=14.08) and second (M=64.95, SD=16.38) round of the experiment (t(10)= -3.773, p=0.003). Although Figure 5.16 shows that the ARA performance improved in the second round for all groups, the paired-sample t-test for G2 and G3 does not show a significant difference. Therefore, I can infer that the individualized VAF helped participants to find previously low-visited charts in a better way than the other two general VAF types.

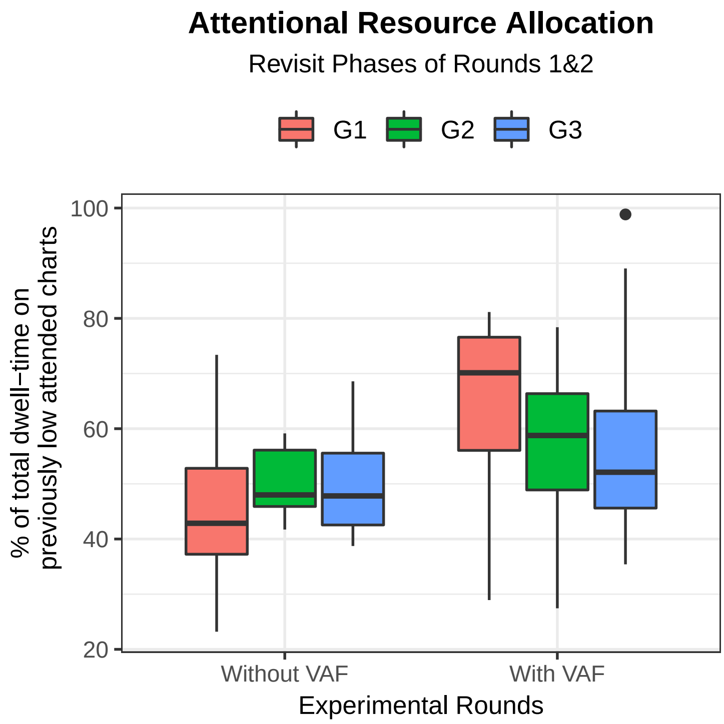


Figure 5.16.: ARA during the revisit phases of experimental rounds.

Moreover, Figure 5.17 shows the ASR for each group. After checking the normality assumptions for transitions, I used the paired-sample wilcoxon test to investigate the effect of VAF types on ASR. For G1, the results reveal that there was a weak significant difference in ASR for the first (M=32.82, SD=17. 86) and second (M=19.55, SD=9.05) round of the experiment (v=56.5, p=0.040). Also, for G2, the results of the paired-sample t-test show a weak significant difference for the first (M=32, SD=16.14) and second (M=25, SD=16.06) round (t(7)=2.3287, p=0.05). However, for G3, the results do not show any significant difference. I can infer that, although the focused attention improved for all three VAF types, the effect of an individualized VAF and an improper VAA example was stronger than the effect of a proper VAA example.

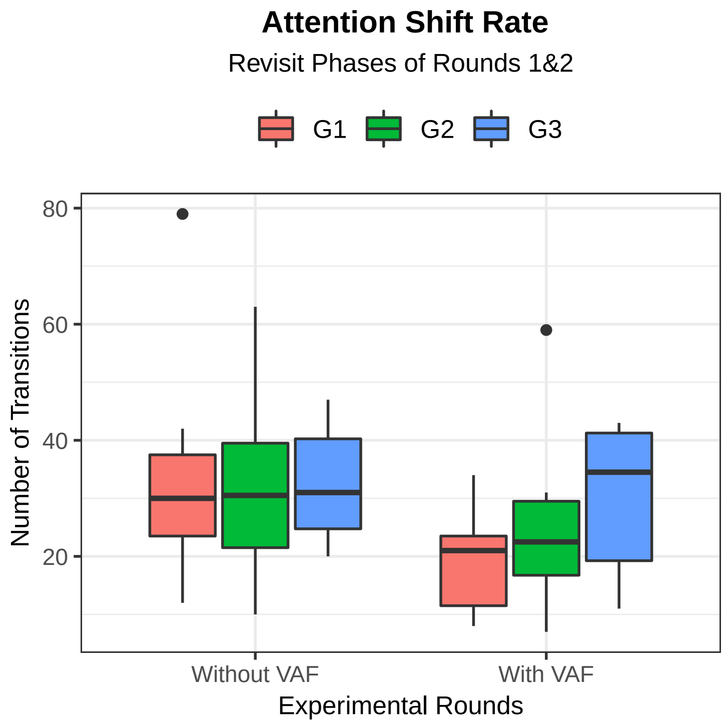


Figure 5.17.: ASR during the revisit phases of experimental rounds.

5.2.5. Discussion

Results from this eye tracking pilot study reveal that individualized VAF supported users to improve both ARA performance and the ASR in comparison with proper or improper examples of ARA as general VAF types. Providing actual values of previous ARA supports users recalling this information from their memory in a better way than receiving the general hints. These results confirm that users with general VAF types had difficulty to recall their previous ARA and to plan for the revisit phase. Regarding the ASR, I found that giving the individualized and improper example of ARA as VAF types supports users in focusing better on the task. However, having a proper ARA example influences neither the ARA performance nor focused attention. The results explain that having an improper ARA example as a hint helps users to better focus during the revisit phase than the proper ARA example. Following the categories highlight in the conceptual framework from in Study I, the individualized VAF has the focus on user adaptation by increasing their awareness about previous visual behavior. Therefore, I conclude that the suggested initial MRs for designing attentive information dashboards that support data exploration tasks with individualized VAF is supportive.

Although the existing results provided valuable findings that help the next steps of this DSR project, this study has some limitations that can be covered in future investigations. This study is considered as an exploratory study to get preliminary results of using the three suggested VAF types. Next, there is a need to differentiate the effects of these VAF types on a large-scale for robust theorization and confirmatory studies. Primarily there is a need to conduct experiments for the individualized VAF since there is evidence that it can support users better than the other general VAF types.

5.2.6. Summary

In the Study III, I cover the remaining stages of the first design cycle. This study focuses on providing solutions for attention management problems in the data exploration task by integrating eye tracking technology. Here, the initial MRs for designing attentive information dashboards are identified, and three types of suggestions for attention support features are presented. Following the categories highlight in the conceptual framework from in Study I, the primary focus of suggestions are on user adaptation by increasing their awareness about previous attention allocation. I propose three suggestions for VAF by integrating real-time and off-line recordings of eye movement data and testing the suggestion in an eye tracking pilot study. So far, eye tracking technology was mainly used to evaluate artifacts by investigating the user's visual behavior of the user (Riedl et al., 2017) rather than using them to design neuro-adaptive IS applications suggested by IS researchers (Davis et al., 2014; vom Brocke et al., 2013). Furthermore, these devices are proposed as the primary method for designing AUI that supports users in managing their limited attentional resources (Bulling, 2016). In this study, I focused on designing attentive information dashboards and VAF that contributes to the IS field by enhancing user capabilities (Dimoka et al., 2012) in managing their limited attentional resources. Following suggestions from vom Brocke et al. (2013), in this design cycle, I focused on both the design and evaluation of three suggested VAF types with eye tracking technology. Furthermore, based on the list of possible contributions in the field of NeuroIS provided by Riedl and Léger (2016), this design is related to the eighth contribution, using NeurosIS tools and delivering an IT artifact which tracks and adapts to the user's attentional state. Moreover, I contribute to the ninth contribution by providing individualized VAF as a live bio-feedback that helps users better control their limited attentional resources. In the second design cycle, I focus on improving the design for individualized VAF and investigating its effect on users' ability to manage limited attentional resources in a large-scale experiment for robust theorization and confirmatory study.

6. Design Cycle 2: Attentive Information Dashboards for Data Exploration [1]

6.1. Study IV: Overview

As the users' attention is known as a limited resource (Chun et al., 2011), users cannot attend all stimuli at the same time and need to select on the specific part of while exploring UIs. UI designers try to overcome this limitation by directing users' attention to important items. They attract users' attention by integrating specific design elements (e.g., size, color, animation, etc.) with UI designs considering the user's specific tasks. Treisman and Gelade (1980) discussed these elements and the role of them as the feature integration theory of attention. Also, in the IS research, several studies focused on investigating the role of such guiding representation on users' attention, such as Cheung et al. (2017) and Hong et al. (2004a).

However, in some tasks like data exploration tasks, a comprehensive overview of all information presented on the UI may be required. Users need to scan complex displays systematically to extract the relevant information (Proctor and Vu, 2006). In these tasks, users need to conduct several attention shifts to allocate their attention to all information rather than on guided attention by specific design features. The attention shifts of users can be different based on their tasks (Yarbus, 1967). Therefore, to process all information on the UI, they need to manage their limited attentional resources by themselves. This is similar to the data exploration task on information dashboards. Providing well-designed information dashboards that enable the exploration of data and support proper decision making is emphasized by Gartner–Magic Quadrant for BI&A systems Cindi et al. (2019). However, even with a proper design, users can only focus on a limited set of information and miss other parts while exploring dashboards (Alberts, 2017; Dilla et al., 2010). The results from the Study II confirms that users have difficulty in managing their limited attentional resources while exploring information dashboards. Therefore, there is a need for designing innovative information dashboards that provide support for managing attentional resources in data exploration tasks.

In the Study III of this thesis, I investigated two common approaches for providing attention support using eye movement data for data exploration tasks. These approaches either use off-line recordings of eye movement data from other users and provide VAF or use real-time eye movement data for individualized VAF. I tested these two approaches in an eye tracking pilot study, and the results show that providing individualized VAF is more supportive that the off-line records. Furthermore, investigating the papers collected in Study I with the focus on supporting data exploration on different platforms has shown that using eye trackers to provide feedback about ARA supports users in improving their self-awareness and therefore their performance. For example, Sharma et al. (2016) has shown that a gaze-aware feedback tool significantly improved ARA and students' learning gains. D'Mello et al. (2012) has found that informing students about their information

[1] This Chapter is based on the following working paper: Toreini et al. (2020c)

processing behavior supports reorienting their attentional patterns and promotes learning, motivation, and engagement. Sarter (2000) has shown the need for giving feedback for effective ARA to support users managing their limited attention while working with highly complex information-rich environments. Deza et al. (2017) demonstrated the benefit of using eye trackers to improve users' performance in a visual search task since the huge amount of data makes operators susceptible to information overload and ARA inefficiencies. Qvarfordt et al. (2010) and Sridharan et al. (2012) investigated using eye movement data as feedback to improve the inspection method in applications such as radiology and imaginary analysis.

As discussed in Chapter 1, Section 1.2, it has shown that the usage of eye trackers for designing individualized VAF is a research gap in IS. The results from Study III show the effective role of individualized VAF for the data exploration task. However, there is a lack of design knowledge describing how to design individualized VAF for information dashboard users to enhance their ability to manage limited attentional resources. Also, there is a need for a confirmatory study about the effectiveness of individualized VAF in a large-scale experiment as a suggested method to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012). Therefore, I focus on the fourth RQ in this thesis as follows:

> ***RQ4:*** *How to design attentive information dashboards providing individualized VAF to enhance users' ability to manage attentional resources for data exploration tasks?*

As Figure 6.1 shows, I focus on the second design cycle of the DSR project in this study. After highlighting the need for such support in Chapter 1, Section 1.1, Section 1.2 and Study II, I continue this design cycle by proposing two theory-grounded DPs. Next, I instantiate both DPs in a software artifact and evaluate them in a large-scale laboratory experiment. Specifically, I analyze users' eye movement data while exploring the information dashboard in the first visit, after receiving the individualized VAF (revisit phase) and at the end of the task. I compare users that received individualized VAF with users that received general VAF in the form of a simple text explanation about the importance of proper ARA while exploring the dashboard.

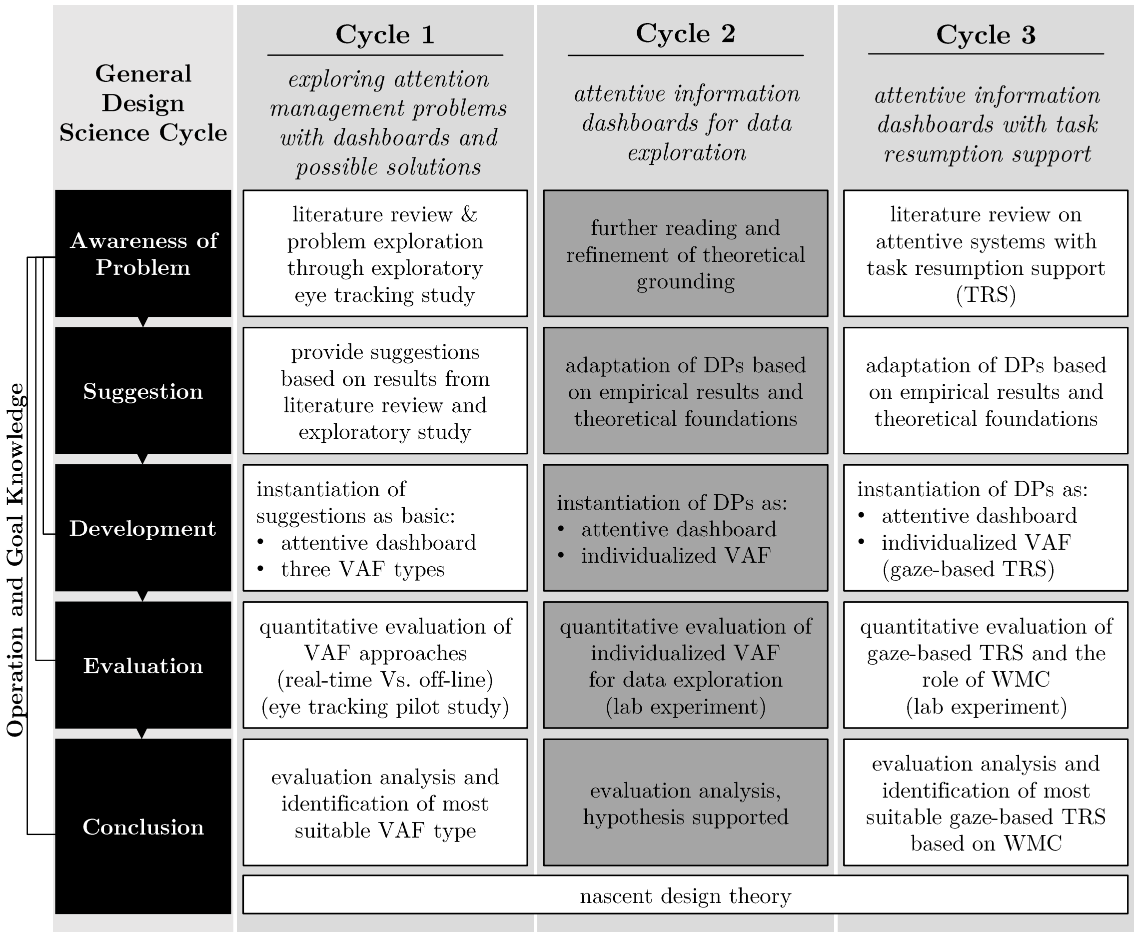


Figure 6.1.: The focus of Study IV in this DSR project.

6.2. Meta-requirements and Design Principles

In the first design cycle, I identified initial MRs to design innovative information dashboards that support data exploration (Study II). Also, I provided initial MRs for designing attentive information dashboard with VAF (Study III). Besides, I found preliminary evidence for the effectiveness of individualized VAF that works with real-time eye movement data in comparison with general VAF that works with off-line records of eye movement data. In the second design cycle, I investigate the influence of individualized VAF in more detail. I start by refining the theoretical grounding for designing attentive information dashboards and individualized VAF and refined the corresponding DPs.

As the first refined MR, I propose that the system needs to monitor the ARA of users in real-time **(Refined MR1)**. Based on the eye-mind assumption (Just and Carpenter, 1980) user's eye movement data represents their ARA. Scholars have used user's eye movement data as an approximation for overt attention (Kowler, 2011). Also, eye trackers have the capability to collect eye movement data in real-time and use it for designing AUI (Bulling, 2016; Henderson et al., 2013; Majaranta and Bulling, 2014; Roda and Thomas, 2006; Vertegaal, 2003). Tracking the users' eye movement data in real-time provides the opportunity to design innovative IS applications (Davis et al., 2014; Riedl and Léger, 2016;

vom Brocke et al., 2013). Thus, I propose the second refined MR estimating the user's ARA based on eye movement data **(Refined MR2)**. These two MRs lay the foundation for the first DP **(DP1)** as following:

> ***DP1:*** *Provide the information dashboard with the functionality to monitor the users' eye movements in real-time in order to analyze the users' ARA on the information dashboard when performing data exploration tasks*

Being able to monitor users while exploring dashboards is a prerequisite to assist users in improving their ARA. Providing feedback that informs users about their previous ARA increases self-awareness and supports further improvement in information processing performance. Previous research has shown that tracking users and providing real-time feedback can influence users' behavior (Jung et al., 2010). Particularly, it has been seen that such feedback supports users in allocating their limited attentional resources more appropriately and ultimately improves their task performance while working with UIs with huge amounts of information (Deza et al., 2017; D'Mello et al., 2012; Göbel and Kiefer, 2019; Qvarfordt et al., 2010; Sharma et al., 2016; Sridharan et al., 2012). Therefore, I propose the attentive information dashboard should provide VAF to users before they finish their tasks and enable them to improve their information processing performance as the third refined MR **(Refined MR3)**. VAF enables users to recognize their current ARA and potentially adjust it accordingly. The provided VAF should enable users to improve information processing while they explore the presented information. Therefore, the provided VAF needs to be individualized rather than generic as well as being lean and precise. In fact, an individualized VAF should increase self-awareness of the users about their goal-directed attention by presenting their eye movement patterns to them. I assume that having such feedback supports users to identify their attentional failure, such as missing important information. Therefore, I propose the need for individualized VAF as the fourth refined MR **(Refined MR4)**. The proposed third and fourth MRs inform the second DP **(DP2)** as following:

> ***DP2:*** *Provide the information dashboard with the functionality to display individualized VAF based on the monitoring and analysis of the users' eye movement data to support information processing performance.*

Table 6.1 summarizes the design activities of the second design cycle with the four refined MRs and corresponding DPs.

<table>
<tr><th>Design Cycle 1</th><th colspan="2">Design Cycle 2</th></tr>
<tr><th>Initial MR</th><th>Refined MRs</th><th>DPs</th></tr>
<tr><td rowspan="4">Initial MR: The dashboard should support users in management of attentional resources by providing VAF while exploring data.</td><td>Refined MR1: Monitor the ARA of users in real-time.</td><td rowspan="2">DP1: Provide the information dashboard with the functionality to monitor the users' eye movement in real-time to analyze the users' ARA when performing data exploration tasks.</td></tr>
<tr><td>Refined MR2: Estimate the user's ARA based on eye movement data recorded with eye trackers.</td></tr>
<tr><td>Refined MR3: Provide feedback about the users' ARA to enable self-awareness.</td><td rowspan="2">DP2: Provide the information dashboard with the functionality to display individualized VAF based on the monitoring and analysis of the users' eye movement data to support users in improving information processing performance.</td></tr>
<tr><td>Refined MR4: Provide lean, precise, and non-suggestive VAF by the information dashboard.</td></tr>
</table>

Table 6.1.: MRs and DPs of designing attentive information dashboards that provide individualized VAF for data exploration tasks.

6.3. Development

To map the DPs to design features, I propose the system architecture depicted in Figure 6.2. The system architecture comprises three subsystems. First, the **Information Dashboard Subsystem** connects to the BI&A system and presents information for decision-makers. A dashboard's layout typically comprises visual features (e.g., chart types, table, etc.) and interaction features (check the interaction list by Yi et al. (2007)) (Pauwels et al., 2009). Dashboard designers develop various layouts based on different purposes (e.g., planning, monitoring, communication, etc.) while users have different types of tasks, levels of knowledge and personality (Yigitbasioglu and Velcu, 2012). Moreover, users typically interact with a dashboard using the mouse, keyboard, or touch to explore the dashboard or search for specific information.

Second, the **Eye Tracking Subsystem** establishes a connection to the eye tracker and provides the functionality to track and store the users' eye movement data to extract the attentional states of users. Previous studies have followed different ways for extracting users' cognitive states as well as attentional status from the user's gaze data (Duchowski et al., 2018; Kowler, 2011). This subsystem provides the ability of real-time extracting of attentional states from users' collected gaze data.

Third, the **Attention-aware Subsystem** focuses on merging the user's attentional state with the dashboard layout and provides individualized VAF. In this subsystem, the attention analyzer component uses information from the eye tracking subsystem besides the visual features' coordination and interactions' log data from the information dashboard subsystem to derive the user's attentional spotlight. Hence, the dashboard becomes sensitive to the user's attention.

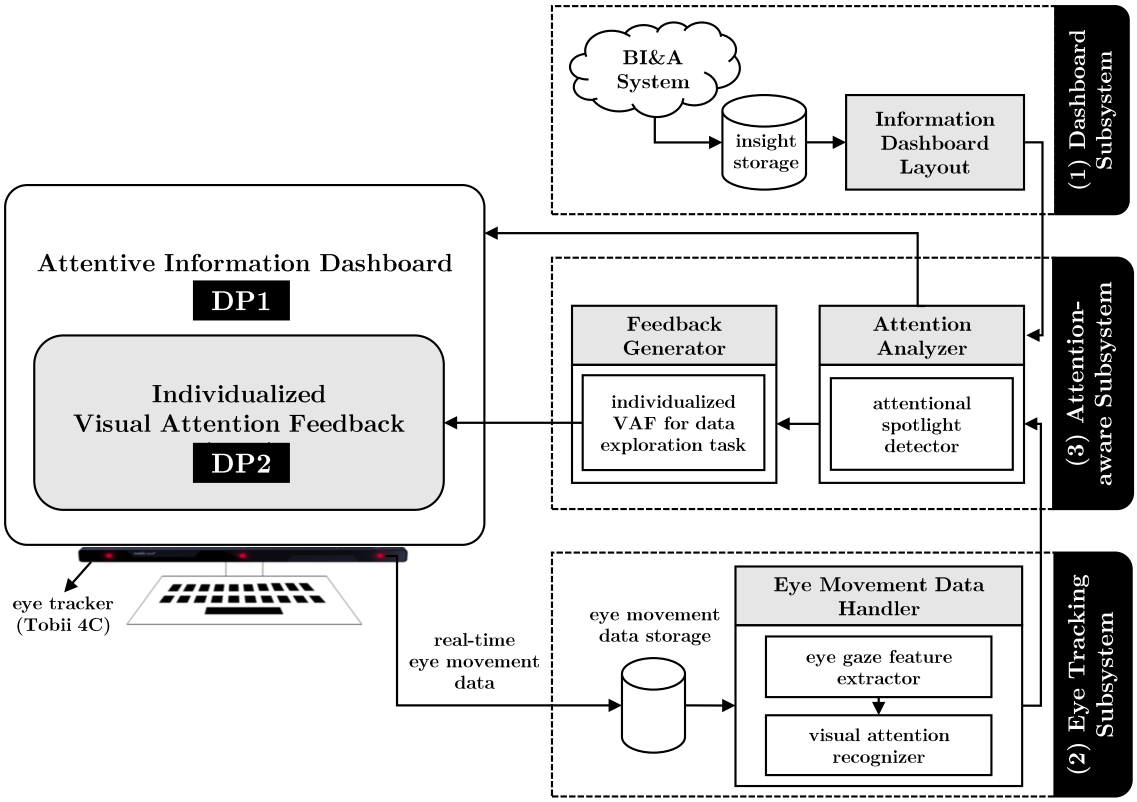


Figure 6.2.: System architecture for designing attentive information dashboards that support data exploration tasks.

I map the DP1 to the attentive information dashboard and the DP2 maps to the individualized VAF capability, building on the feedback generator component. The specific individualized VAF design can vary based on the feedback's purpose and the user's task and characteristics. In this study, I focus on supporting users in better information processing by allocating limited attentional resources properly while conducting data exploration tasks. Therefore, the individualized VAF should present the summary of previous ARA behavior to the user to increase self-awareness. To reach this goal, DP2 is instantiated by presenting the actual gaze duration on each visual feature (e.g., chart, tables, etc.) on the dashboard in a time format. I assume that providing such information enables users to assess their previous ARA and subsequently improve it in case it is needed. Figure 6.3 shows an instantiation of individualized VAF that exhibits the user's gaze duration on a dashboard with six visual features. Besides the individualized VAF, the following general text-based explanation was provided:

> "Many users have a problem to allocate their attention properly while using information dashboards. In the following, you can see your attention allocation so far based on the time that you looked at each chart. Please think about your attention allocation performance in the previous step and then you will have one more minute to continue exploring the dashboard".

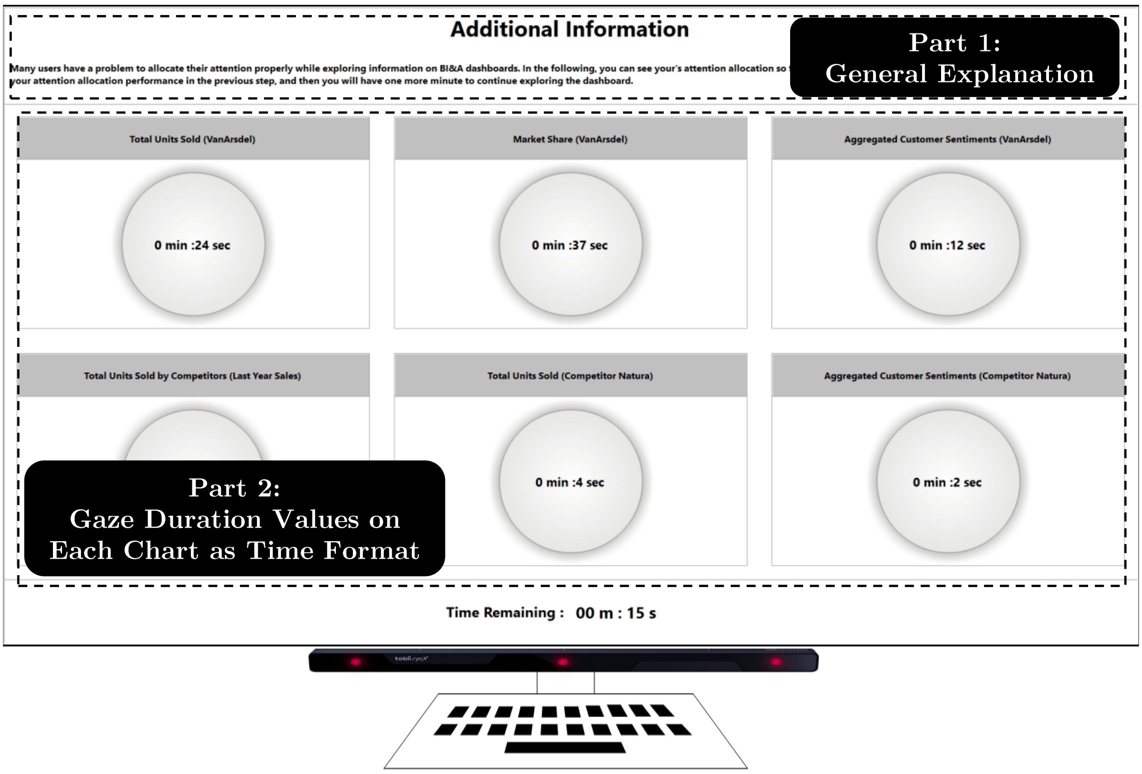


Figure 6.3.: Instantiation of DP2.

Furthermore, I designed a general VAF to compare it with individualized VAF. The general VAF uses similar text as in the explanation part of the individualized VAF. However, I do not provide any further information about individualized gaze duration values. I assume that providing such information supports users to think about their information processing performance and let them judge internally about potential weaknesses. The general VAF shows only a generic text as follows:

> “Many users have a problem to allocate their attention properly while using information dashboards. Please think about your attention allocation performance in the previous step and then you will have one more minute to continue exploring the dashboard”.

6.4. Hypotheses

Figure 6.4 depicts the underlying research model to study the impact of the suggested DPs in this DSR project. As can be seen, I compare two design configurations with DP1&2 activated (individualized VAF) and deactivated (general VAF). I investigated the users’ information processing in three different phases, including the first visit phase, revisit phase,and end of the task. The first phase refers to the first time to explore the dashboard and the period before receiving one of the VAF types. The revisit phase is the period that is used to explore the dashboard after receiving one of the VAF types. Also, I consider the end of the task as the last period for the whole experiment (first and revisit phases). I consider the first visit as a control phase, which demonstrates that users have the same initial visual behavior. Subsequently, I propose hypotheses based on the users' attention after receiving the VAF types (revisit phase and end of the experiment).

To allocate an appropriate ARA in the revisit phase, first, users need to recognize their ARA in the first visit with the support of VAF. Previous research has shown that users have difficulties to remember their previous ARA and repeat their visual behavior in the revisit phases (Cane et al., 2012; Monk et al., 2008; Singh, 1998). Therefore, I argue that users with general VAF have challenges in finding an appropriate revisit strategy in comparison with users that receive individualized VAF. Users with an individualized VAF obtain the memory aid. Previous research has shown that providing VAF guides users to recognize high and low-visited parts of the UI (Göbel and Kiefer, 2019; Qvarfordt et al., 2010) and optimize their behavior in the next steps. Therefore, I define the first hypothesis **(H1)** as following:

> ***H1:*** *Providing individualized VAF results in better* ARA performance in the revisit phase in comparison to providing generic VAF.

Moreover, having a proper strategy in the revisit phase leads to centering attention on specific elements on the dashboard rather than switching between different elements. It has been shown that providing VAF increases user's focus while conducting tasks (D'Mello et al., 2012). Centering attention results in having less ASR by users rather than shifting among different parts of the interface. Therefore, I define the second hypothesis **(H2)** as following:

> ***H2:*** *Providing individualized VAF results in less ASR in the revisit phase in comparison to providing generic VAF.*

Also, previous research has shown that the stimulus' position in the UI affects how users allocate attention to them (Haugtvedt and Wegener, 1994; Lorigo et al., 2008; Nielsen, 2006). It has been seen that users are processing the information similar to the *"F"* pattern. In fact, users start from the left side of the UI and then allocate less attention to the information that comes later on the right side. A recent eye tracking study about dashboards by Tableau (Alberts, 2017) showed that users typically focus their attention on specific areas and thereby potentially miss other parts of the dashboard. Also, the results from the Study II in the first design cycle show that the users are typically analyzing the charts on the left side of the dashboard more intensively. Therefore, I argue that having individualized VAF withdraw users from focusing only on specific areas and support them to have better ARM. I define the third hypothesis **(H3)** as the following:

> ***H3:*** *Providing individualized VAF results in better ARM at the end of the task in comparison to providing generic VAF.*

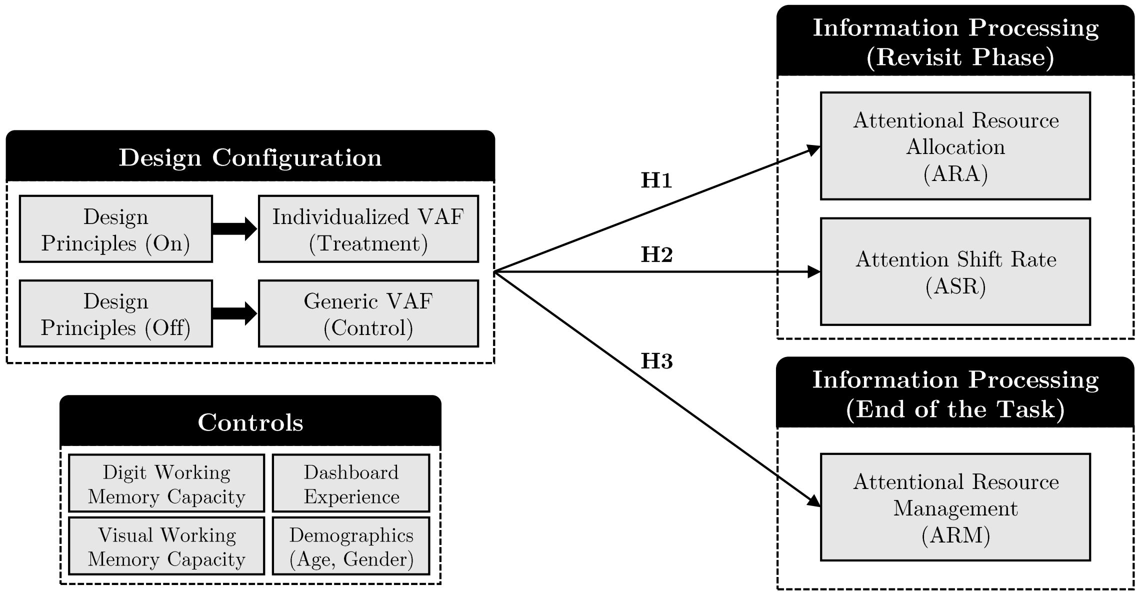


Figure 6.4.: Research model to investigate the effect of DP1&2.

6.5. Laboratory Experiment

6.5.1. Experimental Software and the Apparatus

To prepare the experiment, I first developed the software artifact. This artifact instantiates DP1&2 incorporating the functionalities for tracking the user's eye movement data in real-time. Furthermore, it collects the data required for further analysis in the evaluation section. As an apparatus that enables both tracking users' eye movement data in real-time and record the relevant eye movement data, I used Tobii 4C eye tracker with the corresponding license to store the data. This eye tracker has the sampling rate of 90 Hz and is considered one of the low-cost eye trackers in the market (Farnsworth, 2019). I selected this eye tracker since I argue that the usage of such devices for designing AUI is applicable for daily working tasks and on large-scale. Furthermore, the results from the Study I shows that this is the primary device for designing systems that integrate real-time eye movement data. I connected the eye tracker to a computer that displays the dashboard on a 21-inch screen with a resolution of 1920x1080 for all participants. I developed the experimental software in the .NET framework by using C programming language since Tobii provides the relevant Software Development Kit (SDK) for developing gaze-aware UI (Tobii Core SDK) and collecting data for research purposes (Pro SDK) on this framework. Also, for calibrating the eye trackers, I used Tobii Pro Eye Tracker Manager before running the developed software artifact. To extract the fixations and visualize heatmap in the data analysis section, I used PyGaze (Dalmaijer et al., 2014) as an open-source toolbox for eye movement analysis.

Since the quality of the research design should be judged on the basis of the factors that affect users' ARA, I maintained internal validity from four different perspectives in the experiment. *First*, I evaluated artifacts in a laboratory experiment, ensuring high internal validity by minimizing the influence of external factors that affect the user's performance. *Second*, I minimized the influence of external factors that could affect the quality of collected eye movement data, such as movements and light conditions. For that, I controlled the calibration's quality several times during the experiment with the developed experimental software. *Third*, I used the collected eye movement data to select the users that conducted the experimental task as I asked in the instruction. Based on that, I removed a few users that ignored processing the dashboard or eye tracker could not collect their eye movement data. The dataset includes the participants who process the information dashboard for a minimum of 75 percent of the total dedicated time on each step.

Fourth, I controlled the elements that affect the stimuli-driven attention of the users while exploring. Figure 6.5 displays the dashboard layout that I designed and used for this experiment. As can be seen, this dashboard includes six charts, which I designed in a way to have almost similar complexity from their appearance. To reach that, all six charts have the same type (bar chart) to minimize potential distractions of the visualized format (Kelton et al., 2010). Moreover, all charts, words, and numbers have an equal size to avoid size influence (Alberts, 2017). Also, all charts include six chunks of information as a well-designed visualization promotes chunking (Patterson et al., 2014). I chose six chunks as seven (plus or minus two) chunks of information is known as the maximum capacity for individuals' WMC (Miller, 1956). To control the influences of attention by interactive options (Zhicheng Liu and Stasko, 2010), the dashboard includes only static charts. Besides, the gray color with the same variation is used in all AOIs to manage for color impacts on attention (Bera, 2016). Therefore, with the same visualization format, size, the number of chunks, no interactive options, and gray color, I argue that the six charts have an almost similar complexity from an information representation perspective. In this study, I also collected and analyzed the users' eye movements based on pre-defined AOIs on the dashboard. The dashboard includes six charts, and I consider each of them as one AOI. As Figure 6.5 shows, I named six AOIs based on their position on the dashboard layout. I use AOI's naming to discuss the results in the following sections.

Using elements that influence the users' stimulus-driven attention is common in the real-world dashboards and highly impacts ARA of the users (Alberts, 2017; Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). I acknowledge that a dashboard with the same complexity of all charts does not represent a real-world scenario. However, this design empowers to track the goal-directed attention of the users, as discussed in Chapter 2, Section 2.2.1. I followed this approach to maintain internal validity for the ARA, ASR, and ARM of the users and not a biased one based on stimulus-driven attention. Furthermore, I focus on the overt attention of the users by tracking their eye movement data.

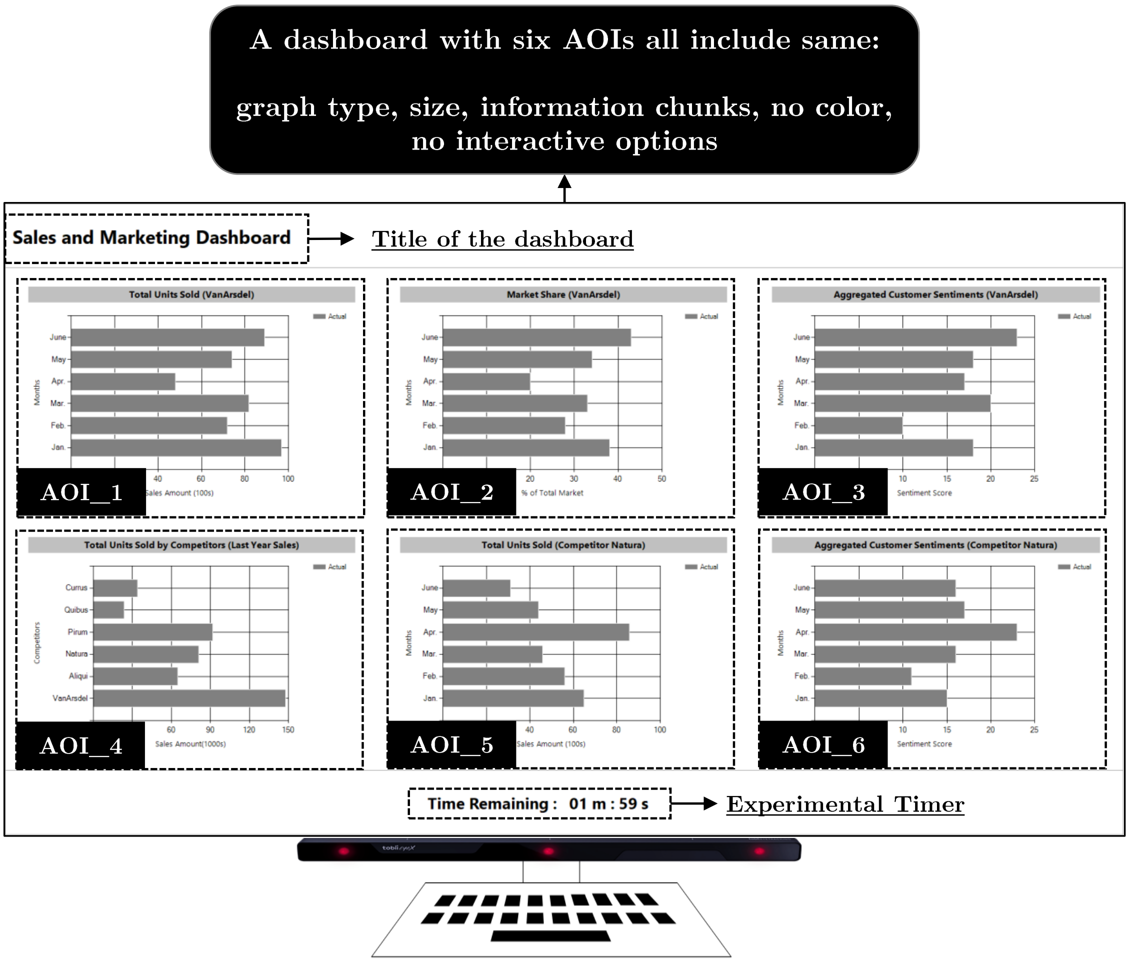


Figure 6.5.: The designed information dashboard to control for stimulus-driven attention.

6.5.2. Experimental Design

To evaluate the effects of the DPs on dashboard users, I instantiated them in a running software artifact and conducted a laboratory experiment. For that, I applied a mixed model design with two groups (DP1&2 activated with individualized VAF and DP1&2 deactivated with general VAF) as between subjects and time (before and after receiving the VAF types) as the within-subject. I assigned participants randomly to either individualized VAF (treatment condition) or general VAF (control condition) before the experiment. Both groups had the same task in the experiment, and I limited the execution time in each experimental phase.

I started the experiment by calibrating the eye trackers using Tobii Pro Eye Tracker Manager. Next, the participants started a screen-based instruction that introduced different steps of the experiment. As a scenario, I told participants to imagine themselves as sales managers in a company. They recently joined the sales organization and are about to have a meeting with their boss. A few minutes before the meeting, they received the last six months' sales report in the form of an information dashboard. They required to prepare for this meeting by exploring the company's status with regards to sales data. Furthermore, I informed them about the experiment's timing and let them know that the experimental software included a timer for tracking the remaining time for each step. The instruction ended with control questions to ensure that participants understood the experimental steps and the provided information on the dashboard appropriately. Next, I provided a simplified variant of the dashboard used in the experiment without VAF (Check Appendix D, Figure D.1. This version included a dashboard with only two charts and supported users to get familiar with the experimental task and steps. Next, I asked them to rest for two minutes before starting the main part of the experiment. I added this break to control for carry-over effects between the trial and the main part of the experiment.

Figure 6.6 shows the steps for the main part of the experiment. In the *"First Visit Phase"* of data exploration, participants received the dashboard and explored it for two minutes. The information dashboard for this study can be seen in Appendix D Figure D.2. After that, they were interrupted for 30 seconds. In this step, participants received one of the two designed VAF types (individualized VAF or general VAF) based on the group that they were assigned randomly before the experiment. Examples of these VAF types can be seen in Appendix D, Figure D.3 and D.4. Later, in the *"Revisit Phase"*, the participants were asked to revisit the same dashboard for one more minute. In the last step, participants answered typical demographics questions. Next, I asked them to rest for a few minutes and get ready for WMC tests. Finally, the two WMC (Corsi span and Digit span) tests were performed using the PEBL test battery (Mueller and Piper, 2014).

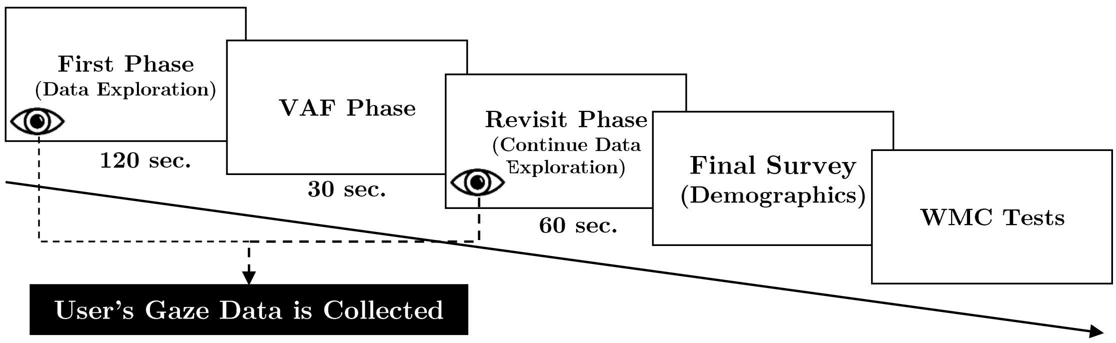


Figure 6.6.: The experiment's procedure used to evaluate the effects of DPs.

6.5.3. Participants

In total 92 university students (35 female, 57 male) with an average age of 23.45 (SD=3.39) participated in this experiment. I used student participants for the laboratory experiment, as this comes with two key advantages. First, in contrast to employees in organizations, students are not specifically trained in working with dashboards and are not biased from contextual information. Therefore, they have – similarly to novice users – little or no prior knowledge of the underlying experiment's process. Second, it is easier to reach student participants in a relatively large sample size with reasonable effort to achieve adequate statistical power. Consequently, students can be considered an adequate and representative sample in the experimental setup (Burton-Jones and Meso, 2008).

The students received 10 Euro as a financial incentive for participating and completing the experiment. I recruited participants from an experiment pool and randomly assigned 48 participants to the control group (general VAF) and 44 to the treatment group (individualized VAF). The initial number of participants was 107, but 15 participants were removed from the sample. For 12 participants, the available recorded eye movement data was less than 75 percent of the overall time (basically less than 90 seconds in the first visit or less than 45 seconds in the revisit phase). I assume that these 12 participants did not seriously engage in the data exploration task, or the eye tracker had technical problems recording their eye movement data. Two participants were excluded from the dataset because they did not correctly answer the control question in the post-experimental survey. Finally, I excluded one more participant because of self-reported health problems with the eyes.

6.5.4. Measurements

I measured several dependent and control variables during different steps of the experiment. Table 6.2 displays a summary of all measurements used in this study.

	Construct	Definition	Measurement	References
Information Processing (Revisit Phase)	Attentional Resource Allocation (ARA)	Users performance in allocating attention on previously low-attended AOIs and ignore previously high-visited AOIs	Eye Tracking (fixation duration, number of fixations)	(Just and Carpenter, 1980) (Cheung et al., 2017) (Qvarfordt et al., 2010)
	Attention Shift Rate (ASR)	The number of directing attention while processing information	Eye Tracking (total number of transitions pairs)	(Hong et al., 2004) (Blascheck et al., 2014)
Information Processing (End of the Task)	Attentional Resource Management (ARM)	The ability to distribute the attention properly among all stimulus on the screen	Eye Tracking (variance of fixation duration and number of fixations on six AOIs)	Self-defined
Controls	Visuospatial WMC	The capacity of user's visuo-spatial memory	Corsi Span	(Kessels et al., 2000)
	Digit WMC	Capacity of users regard to memorizing digit numbers	Digit Span	(Conway et al., 2005)
	Demographics	Gender, Age, Experience level	Survey	Self-defined and (Moore, G.C. 1989)

Table 6.2.: The dependent variables and controls used in Study IV.

As the dependent outcomes, I explored users' ability to manage limited attentional resources regarding ARA, ASR, and ARM. I measure the users' ARA following the approach used by Cheung et al. (2017). Based on this study, user's fixation duration and the number of fixations on each pre-defined AOIs are known as the user's ARA on that AOI. To recognize the user's performance on their ARA, I compared the fixation duration and number of fixations of the first visit with the revisit phases based on six AOIs. By chance, each chart would receive (100/6=16.67 percentage) of the ARA. This was subtracted from the actual ARA percentage, therefore yielding a score reflecting whether a given AOI was attended more (or less) than the theoretical average. I consider the revisit phase as the opportunity to enhance information processing performance. Therefore, the better performance results in having higher ARA on the previously low attended charts in the revisit phase. Furthermore, I measured users' ASR in the revisit phase. This measure is considered as centering of attention on a limited stimulus that exists in the field rather than shifting attention among all of them. It assumes that when the users have a clear strategy for visiting the information dashboard, they have less ASR. The eye tracking researchers have used the ASR of users among AOIs to explain how focused is user's attention (Bednarik and Tukiainen, 2006; Ishii et al., 2013). The ASR between AOIs is measured by the number of transitions, which is the movement of eyes from one AOI to another (I ignored the transitions within the same AOI). Consequently, the transition matrix represents the ASR between all possible combinations of AOIs (Ponsoda et al., 1995). In fact, the transition matrix is a descriptive summary representation of collected data that supports the analysis of users' data exploration behavior (Blascheck et al., 2014; Burch et al., 2011; Kurzhals et al., 2016). Furthermore, I measured the users' ARM at the end of the data exploration task. As explained in Section 6.5.1, all six AOIs on the dashboard have the same complexity and importance level from the presentation style. Therefore, I consider a more even distribution of attention on all six AOIs as a better ARM performance. For that, I calculate the standard deviation between fixation durations and the number of fixations on all six AOIs at the end of the data exploration task. Lower standard deviation values intimate that these six numbers are closer to each other, and the user properly distributed attention. Also, a higher standard deviation value demonstrates lower ARM.

Second, I measured several participant-specific control variables (demographics as well as two different WMC types). Regarding demographics, I captured gender, age, and compatibility with previous experience (Moore, 1989) to work with dashboards through survey questions (Appendix D in Table D.1). I considered the users experience since it plays a role in users eye movement data and managing limited attentional resources while exploring visualized information (Gegenfurtner et al., 2011). I also measured the users' WMC from two perspectives. The reason for choosing WMC as a control variable is its importance with regards to processing information, as described in Chapter 2, Section 2.2. WMC predicts the attention control of users (Kane et al., 2001; Kane and Engle, 2003) and has been defined as one important individual characteristic while working with visualized information (Borkin et al., 2016; Haroz and Whitney, 2012; Healey and Enns, 2012; Toker et al., 2013). Scholars have noted that working memory span tasks are the most proper way to compare the individual's WMC with each other (Conway et al., 2005).

Also, individuals have different capabilities in remembering different information types. Consequently, different working memory spans exist to measure. In this study, I measure two types of users' working memory span as digit and visuospatial WMC. The reason is that dashboard users mostly deal with digits as well as visualized information on the dashboard. I collected the users' visual WMC by running a visuospatial Corsi Block-Tapping test (Kessels et al., 2000) and the digit span test (Conway et al., 2005) to measure the number of digits that can be memorized by a specific user. Both tests report the working memory span value that is the longest sequence a user could correctly repeat in each test. The higher the working memory span value, the higher the WMC.

6.6. Data Analysis and Results

6.6.1. Manipulation and Control Checks

Before testing the hypotheses, I checked whether the random-assignment between-participant conditions was successful or not by testing if the two groups do not differ concerning WMC and the three demographic controls assessed in the final survey.

The chi-squared test for comparing participants' gender per condition (individual VAF and general VAF) was not significant (chi-square=.558, p>.45). Therefore, random assignment for gender was successful. Moreover, the results from the wilcoxon signed-rank test for all the other control variables (age, experience level, Corsi span and Digit span) did not show any difference between the two groups (Appendix D, Table D.2) and the random assignment was successful. Also, to ensure that all users had the same visual behavior in the first visit phase, I analyzed the users' eye movement data and compared ARA, ASR and ARM between two groups. The result shows that users from both groups had similar visual behavior before receiving VAF types. I present the details in the following sections.

6.6.2. Attentional Resource Allocation

Figure 6.7 shows the heatmaps based on the user's ARA within both groups. The left column displays the ARA of the first visit phase, and the right column shows the revisit phase. In the first visit phase, visual behavior did not differ between the groups and the ARA was influenced by the position of the AOIs. For both groups, the left charts (AOI-1, AOI-4) received more attention than the one in the middle (AOI-2, AOI-5) and the middle AOI received more attention than the right side (AOI-3, AOI-6). Also, a column-based observation reveals that charts on the first row (AOI-1, AOI-2, AOI-3) have a higher ARA in comparison to the corresponding charts in the second row (AOI-4, AOI-5, AOI-6). These results confirm that the users are biased to allocate their attention to the left and top of the dashboards similar to other UI types (Lorigo et al., 2008; Nielsen, 2006).

During the revisit phase, the results from the general VAF group show that users repeated their visual behavior while the users in the individualized VAF changed it. Investigating through the rows shows that for the general VAF group, the left-sided AOIs have higher values than the right-sided AOIs. Also, column-based investigation indicates that the general VAF group had higher values for the AOIs in the upper position again in comparison with the AOIs in the lower position. However, the users in the individualized VAF group had more ARA to the right-sided AOIs as well as having higher ARA on AOIs positioned in the lower position. Furthermore, the distribution of fixation duration and number of fixation on each AOI can be seen in Appendix C in Figure D.5 and D.6.

Overall, by qualitative analyzing the visual behavior of both groups via heatmaps, I find that users with individualized VAF improved their ARA in the revisit phase, while the users with the general VAF tend to repeat their visual behavior after receiving a second chance to explore the dashboard.

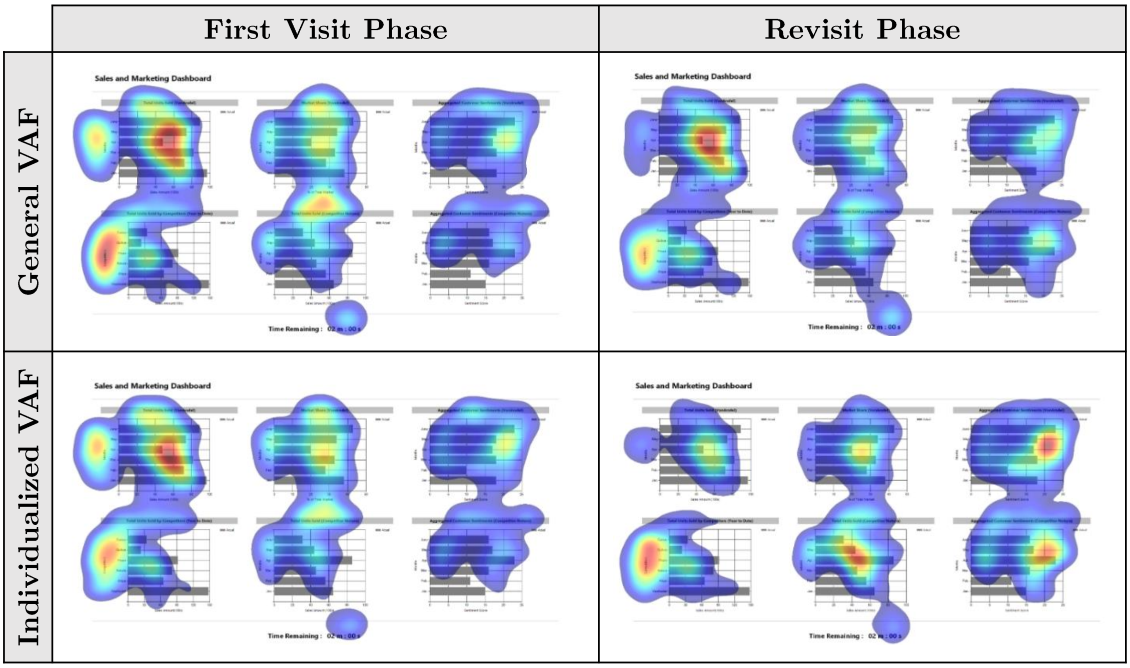


Figure 6.7.: Heatmaps of both groups in the first and revisit phases.

To test the ARA performance hypothesis in the revisit phase (H1), repeated-measures regression analysis was carried out based on the percentage fixation duration and number of fixations. Besides, prior to the analysis, the ARA scores were centered around the mean average percentage (100/6). Following this, zero reflects the average percentage of ARA spend on an AOI at a given point in time. In the first model, I predicted the fixation duration per AOI in the revisit phase from the fixation duration of that AOI in the first visit, the experimental condition (0=general VAF group; 1=individualized VAF group), and their interaction. First, the effect of fixation duration percentage in the first visit was significant, $b=1.145$ percentage, $SE=0.223$ percentage, $t(548)=5.129$, $p<.001$; indicating that in the general VAF group, the fixation duration of an AOI was a strong predictor of the fixation duration of the same AOI in the revisit phase. In other words, participants show consistency in their behavior as expected regard to the fixation duration. Figure 6.8 shows on the left part the positive slope in the general VAF group. An AOI that received a higher percentage of ARA (in terms of fixation duration and number of fixations) in the first visit also received more ARA in the revisit phase. Second, there was a significant interaction of fixation duration percentage in the first visit and the individualized VAF group, b=-0.75 percentage, SE=0.138 percentage, t(548)=-5.468, p<.001. This shows that the effect of the fixation duration of the first visit on the fixation duration of the revisit phase was compensated by the individualized VAF (Figure 6.8, left side). Thus, compared to the general VAF group, an AOI with a high fixation duration in the first visit had relatively less fixation duration in the second phase for the individualized VAF group. Vice versa, a previously AOI with low fixation duration had high fixation duration in the second phase.

Similar to fixation duration, an analogous analysis for the number of fixations also yielded two significant effects: First, the effect of the number of fixations in the first visit was significant, b=1.211 percentage, SE=0.221 percentage, t(548)=5.467, p<.001; indicating that in the general VAF group, the number of fixations on an AOI was a strong predictor of the number of fixations to the same AOI in the revisit phase, and participants show consistency in their behavior regard to the number of fixations. Second, the effect of the number of fixations in the first visit on the number of fixations in the revisit phase was compensated by the individualized VAF (Figure 6.8, right side). Crucially, the results show that there was a significant interaction of the number of fixations in the first visit and the individualized VAF group, b=-0.812 percentage, SE=0.133 percentage, t(548)=-6.067, p<.001.

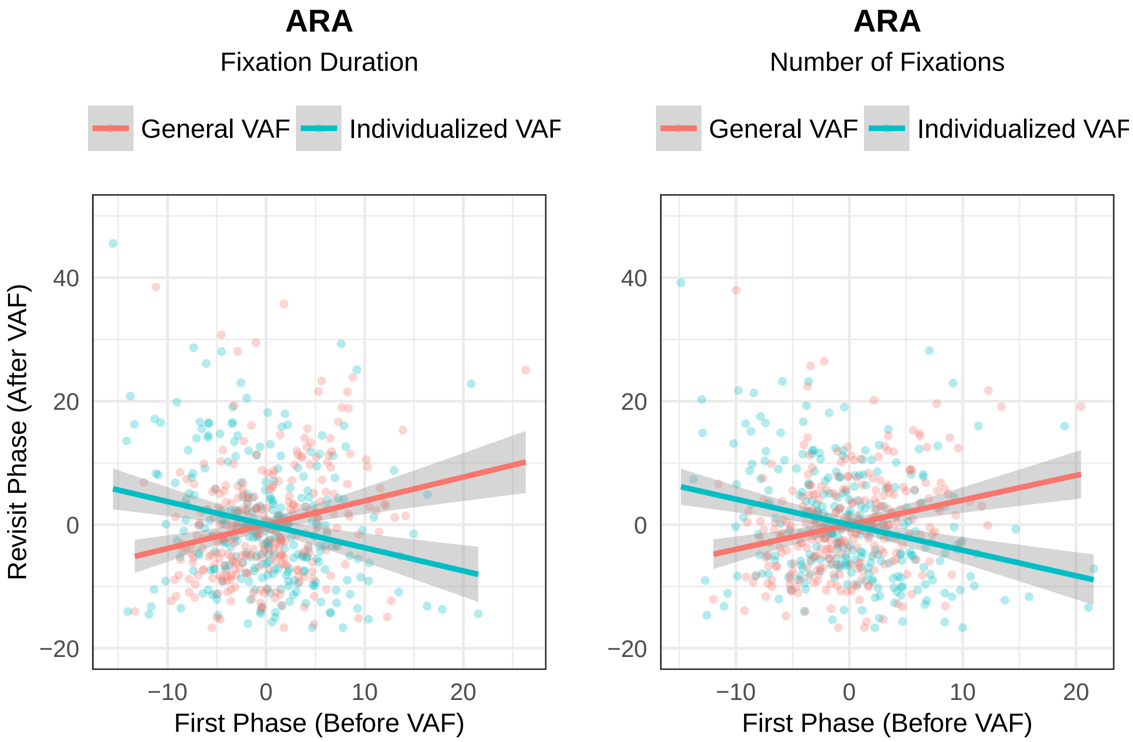


Figure 6.8.: The interaction between and after VAF types for both groups.

To summarize, the results from the qualitative analysis of the heatmap as well as quantitative analysis for fixation duration and number of fixations show that ARA performance of users with the individualized VAF improved in comparison with the users with general VAF. Participants with the general VAF were consistent, and AOIs that were highly attended to in the first phase, also received more attention in the revisit phase. However, for the users with individualized VAF, an AOI that received more ARA (in terms of fixation duration and the number of fixations) in the first visit received less ARA in the revisit phase, and vice versa. Therefore, H1 is supported.

6.6.3. Attention Shift Rate

Figure 6.9 displays the transition proportions among six AOIs in the first and the revisit phase for both groups. In these matrixes, the number in the cell represents ASR in percentage between each possible AOI pairs. The reason to show the proportions rather than the actual number of transitions for each pair is the difference between the data exploration time in the first visit (two minutes) and the revisit phase (one minute). In addition, the color scaling shows the differences between values on these matrixes to ease the qualitative analysis.

General VAF — First Phase

total number of transitions (Mean=83.56 , SD=21.66)

	AOI1	AOI2	AOI3	AOI4	AOI5	AOI6
AOI1	-	9.82%	1.37%	5.53%	2.24%	0.30%
AOI2	10.07%	-	6.51%	1.15%	3.47%	0.55%
AOI3	0.97%	4.99%	-	0.70%	1.05%	6.66%
AOI4	5.46%	1.47%	0.27%	-	5.06%	0.72%
AOI5	2.69%	4.94%	0.60%	4.69%	-	5.41%
AOI6	0.32%	0.62%	5.81%	1.07%	5.48%	-

General VAF — Revisit Phase

total number of transitions (Mean=45.52 , SD=13.67)

	AOI1	AOI2	AOI3	AOI4	AOI5	AOI6
AOI1	-	10.25%	1.24%	5.13%	2.61%	0.37%
AOI2	10.89%	-	6.73%	1.05%	3.52%	0.73%
AOI3	0.87%	5.72%	-	2.29%	0.82%	6.45%
AOI4	4.53%	1.28%	0.14%	-	5.31%	0.82%
AOI5	2.75%	3.84%	0.78%	5.17%	-	5.35%
AOI6	0.46%	1.01%	5.49%	0.87%	5.58%	-

Individualized VAF — First Phase

total number of transitions (Mean=77.66, SD=24.21)

	AOI1	AOI2	AOI3	AOI4	AOI5	AOI6
AOI1	-	10.77%	1.55%	5.50%	2.17%	0.38%
AOI2	10.01%	-	7.37%	0.91%	3.86%	0.70%
AOI3	1.26%	6.00%	-	0.79%	0.88%	5.59%
AOI4	5.74%	0.88%	0.26%	-	5.03%	0.64%
AOI5	2.93%	4.77%	0.70%	4.65%	-	4.77%
AOI6	0.59%	0.67%	4.77%	0.97%	4.86%	-

Individualized VAF — Revisit Phase

total number of transitions (Mean=37.52 , SD=15.38)

	AOI1	AOI2	AOI3	AOI4	AOI5	AOI6
AOI1	-	8.12%	1.45%	3.39%	1.33%	0.48%
AOI2	7.45%	-	6.84%	0.73%	4.18%	1.27%
AOI3	1.21%	5.88%	-	0.79%	1.03%	7.75%
AOI4	3.94%	0.67%	0.36%	-	4.85%	0.85%
AOI5	1.70%	4.24%	0.67%	4.97%	-	7.69%
AOI6	0.73%	1.33%	7.15%	0.97%	8.00%	-

Figure 6.9.: Transition matrix of the users in both groups.

Figure 6.9 shows that in the first visit, both groups had similar investigations by focusing mostly on AOI-1 and AOI-2. However, comparing the transition matrix in the first and revisit phase shows that the users with individualized VAF changed their strategy and investigated the relationship between AOIs on the right side of the dashboard. For this group, the transitions between AOI-5 and AOI-6 have the highest value, while for the general VAF group the transitions between AOI-1, and AOI-2 remain as the highest value. Comparing the heatmaps with the transition matrixes indicates that the users with individualized VAF not only had higher ARA on previously low attended AOIs also investigated the relationships between them more. Also, users in the general VAF group repeated their ARA and investigated the relationship between them instead of focusing on investigating new relationships.

As discussed in Section 6.5.4, the total number of transitions in each phase represents the ASR of the user in that phase. As the time for the revisit phase (1 minute) was lower than the first visit phase (2 minutes), the total number of transitions is lower in the revisit than the first visit phase for both groups. Figure 6.10 shows the amount of ASR for each group before and after VAF. For comparing the ASR in the first visit phase, I conducted an independent t-test between individualized VAF (M=77.66, SD=24.21) and general VAF (M=83.56, SD=21.66) groups that do not show any significant difference t(86.59)=-1.22, p=0.22. Therefore, I argue that both groups had the same ASR in the first visit. However, in the revisit phase, the results from the wilcoxon rank-sum test indicate that users with individualized VAF (Mdn=35) had significantly lower ASR than the users with general VAF (Mdn=45), W= 661.5, p=0.002, r=-0.321. Thus, the analysis of the empirical data also supports H2.

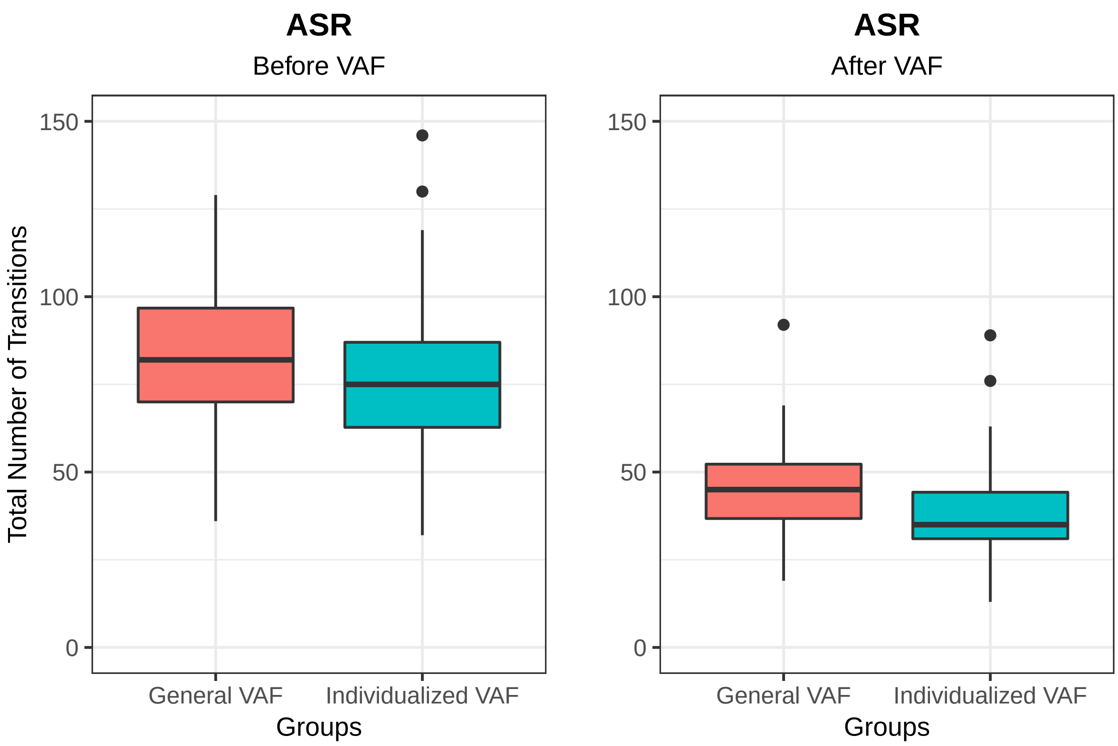


Figure 6.10.: ASR of users before and after receiving VAF types.

6.6.4. Attentional Resource Management

Figure 6.11 indicates the interaction plot for fixation duration and the number of fixations that shows how the ARM of the users changed during the experiment. As can be seen, the ARM of users' with individualized VAF improved massively while it is not the case for users with general VAF (the lower standard deviation values among six AOIs represent better ARM). Furthermore, the amount of ARM based on fixation duration and number of fixations for both groups can be seen in Appendix D and Figures D.7 and D.8

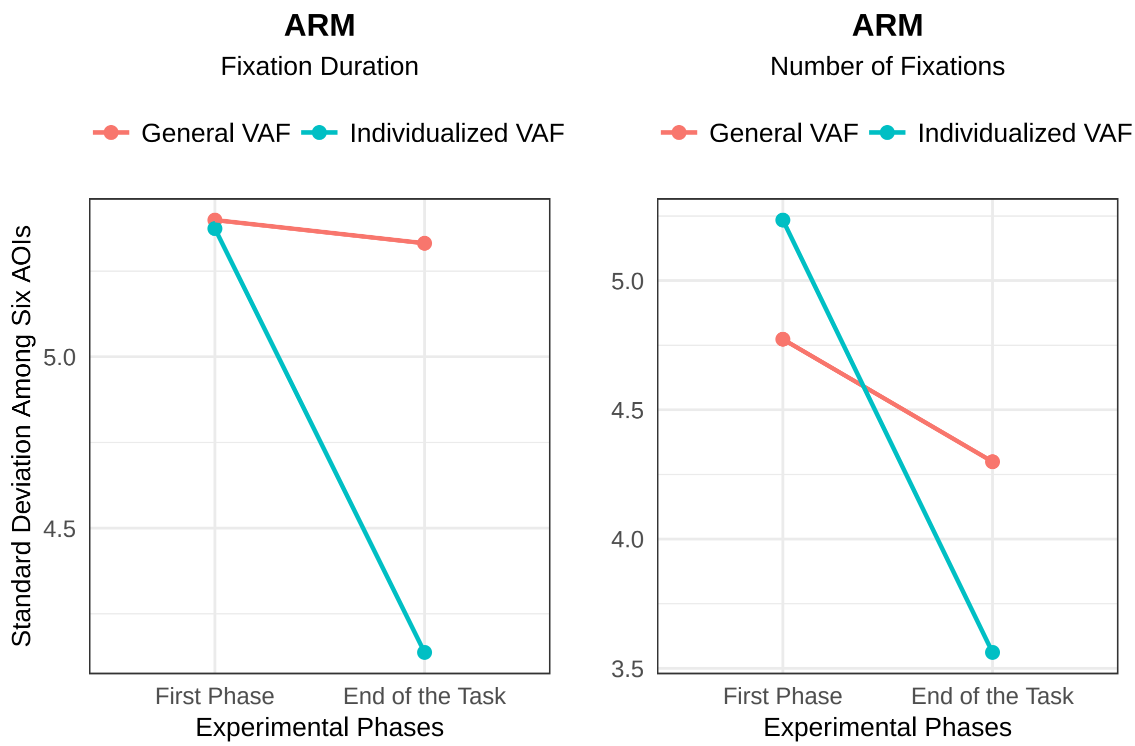


Figure 6.11.: Interaction effect of groups and phases on ARM performance.

To compare the ARM, I first conducted the wilcoxon's rank-sum test to investigate differences between two conditions at the end of the first visit (between-subject analysis). As can be seen in Table 6.3, there is no difference in the ARM of the users between two groups at the end of the first visit phase for both fixation duration ($p=0.77$) and the number of fixations ($p=0.14$). This is aligned with the previous findings that users of both groups have the same visual behavior in the first visit. However, the results show significant difference for both fixation duration ($p=0.01$) and the number of fixations ($p=0.03$) at the end of the task. Second, I investigated ARM by comparing each group in two phases (within-subject analysis). The results from wilcoxon signed-rank test show that the ARM of users with individualized VAF for both fixation duration ($p<.001$) and number of fixations ($p<.001$) differ significantly. However, the general VAF did not support users to improve their ARM significantly.

The findings from within and between analysis of the ARM show that the users with individualized VAF had better ARM than the users with general VAF at the end of the data exploration task. Thus, H3 is supported.

Between Subject Analysis						
DV	**Exp. Phase**	**Condition**	**Median**	**W**	**P**	**R**
ARM performance (based on fixation durations)	End of the First Phase	General VAF	5.4	1019	0.77	-0.029
		Individualized VAF	5.37			
	End of the Task	General VAF	5.33	1364	0.015*	-0.251
		Individualized VAF	4.14			
ARM performance (based on No. of fixations)	End of the First Phase	General VAF	4.77	868	0.143	-0.15
		Individualized VAF	5.23			
	End of the Task	General VAF	4.3	1322	0.037*	-0.216
		Individualized VAF	3.56			
Within Subject Analysis						
DV	**Conditions**	**Exp. Phase**	**Median**	**V**	**P**	**R**
ARM performance (based on fixation durations)	General VAF	End of the First Phase	5.4	754	.089	-0.173
		End of the Task	5.33			
	Individualized VAF	End of the First Phase	5.37	807	<.001 ***	-0.403
		End of the Task	4.14			
ARM performance (based on No. of fixations)	General VAF	End of the First Phase	4.77	767	.066	-0.187
		End of the Task	4.33			
	Individualized VAF	End of the First Phase	5.23	869	<.001 ***	-0.498
		End of the Task	3.56			
Note: * p<0.05, **p<0.01, ***p<0.001						

Table 6.3.: Comparing ARM performance of the users in both groups.

6.7. Discussion

The second design cycle of the DSR project in this thesis includes several steps that discussed in previous sections. Based on that, I first derived MRs and DPs from existing prescriptive knowledge in the AUI field besides descriptive knowledge described in attention and HIP theories explained in Chapter 2, Section 2.2. These DPs focused on supporting users in managing goal-directed attention that refers to the voluntary type of attention (Corbetta and Shulman, 2002). Furthermore, these DPs focus on providing individualized VAF based on overt attention, which can track through an extrinsic behavior such as eye movements (Posner, 1980). Also, the individualized VAF can increase the awareness of the users about previous attention based on the eye-mind assumption that indicates where users are fixating is underlying their cognitive process, such as allocating their attention (Just and Carpenter, 1980). Furthermore, I presented the system architecture to map DPs to design features and provide the fundamentals for the development section. This information can help researchers and practitioners develop attention information dashboards that support data exploration with individualized VAF. Later, the identified key constructs leveraged in this study to measure users' ability to manage limited attentional resources. For that, I focused on measuring the attention of users before and after receiving the individualized VAF as well as at the end of the task. First, I measured ARA in the revisit phase that examines the ability to ignore high-visited charts previously and allocating attention to the previously low-visited charts. I also measured the ASR that investigates the ability to select limited charts to process in the revisit phase rather than allocating attention to many charts. Besides, I measured users' ARM at the end of the task that explains their ability to allocate attention to all dedicated charts on the dashboard properly. Next, I formulated three hypotheses for evaluating the effects of the DP1&2 on the ability to manage limited attentional resources. I tested these hypotheses based on analyzing user's eye movement data. The findings described in the previous section show that the proposed DPs and their instantiation in a software artifact increase ARA and ASR performance in the revisit phase (H1&H2) and ARM performance at the end of the task (H3).

All in all, I can argue that the findings of this experiment reveal that the suggested solution (attentive information dashboards with individualized VAF) to support data exploration tasks on information dashboards help users in managing limited attentional resources. Based on the results from ARA, ASR, and ARM, the users with individualized VAF have a higher level of awareness about their previous visual behavior in allocating attention and could plan to improve it in the revisit phases.

6.8. Summary

The second design cycle of this DSR project is motivated by users' challenges in managing limited attention while exploring information dashboards. I provide a solution for that following the DSR paradigm and articulate theoretically grounded DPs for designing innovative software artifacts, attentive information dashboards for data exploration task. This software artifact tracks users' eye movement data in real-time and provides individualized VAF. Based on Gregor (2006), the proposed MRs and DPs are considered as type V theory contribution (Design and Action), since it gives explicit prescriptions for constructing attentive information dashboards that provide individualized VAF for data exploration tasks. Furthermore, vom Brocke et al. (2013) have emphasized that there are limited contributions in the DSR community that make actual use of the potential of neuroscience tools (e.g., eye tracker) to design advanced built-in functions for IT artifacts. To the best of my knowledge, this design cycle and the proposed individualized VAF is the first project that investigates the integration of real-time eye movement data as a built-in function for IT artifact, in this case, information dashboards.

Furthermore, I evaluated the proposed DPs in an eye tracking laboratory experiment with 92 participants. The findings reveal the positive effect of using individualized VAF on managing limited attentional resources focusing on ARA, ASR, and ARM. The findings described in the previous section show that the proposed DPs and their instantiation in a software artifact increase ARA and ASR performance in the revisit phase (H1&H2) and

ARM performance at the end of the task (H3). It shows that when an information dashboard features individualized VAF, users can manage their limited attentional resources in a better way in comparison with users without such support. Based on Gregor (2006), this contribution is considered as II theory (Explanation) since it provides explanations about the effects of using DP1&2 on enhancing users ability to manage their limited attentional resource during data exploration tasks. According to the DSR contribution framework by Gregor and Hevner (2013), the proposed attentive information dashboards to support data exploration is an improvement since I successfully developed a new solution (DP1&2) to the existing problem (managing limited attentional resources).

7. Design Cycle 3: Attentive Information Dashboards with Task Resumption Support [1]

7.1. Study V: Overview

In the age of information, it is hard to find someone that is not challenged by interruptions. During the last years, many observational studies identified the disruptive role of interruptions in daily life (Borst et al., 2015). The workplace is also accompanied by frequent interruptions of task execution (Czerwinski et al., 2004; Mark et al., 2008). Interruptions are known to have various negative impacts, such as higher task completion time, the number of errors, or anxiety in multitasking situations (Borst et al., 2015,1; Czerwinski et al., 2000; O'Conaill and Frohlich, 1995). Even though task disruptions can sometimes be unavoidable, e.g., due to the importance of the secondary task or the specific context of work (Dostal et al., 2013), it is necessary to design systems that provide advanced support in better managing interruptions (Anderson et al., 2018).

In the domain of HCI, research on interruptions and task resumption has a long tradition. Several studies focused on explaining how users are coping with that (Borst et al., 2015; McFarlane and Latorella, 2002). In a multitasking environment, users need to shift their attention from the primary task to the secondary task and allocate their attentional resources to the execution of the secondary task. Afterward, users need to shift their attention to the primary task once again, which is sometimes challenging due to remembering previous behavior and resuming the primary task properly. Therefore, capturing and remembering representations of tasks may be useful to assist users in switching among them. A promising solution supporting users in better managing interrupted tasks are AUIs (Anderson et al., 2018; Bailey and Konstan, 2006). Leveraging such a system to detect an interruption and provide TRS by highlighting previously attended areas proved to support users in managing attention (Göbel and Kiefer, 2019; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). Eye tracking technology is known as a tool to provide TRS. Researchers have used this technology to track the user's eye movements to understand the moment of task switching (Chen et al., 2013) and subsequently visualize the user's eye movement data as an indicator of the most recent attention area (Dostal et al., 2013; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). Gaze-based TRS makes previous cognitive processes more explicit by providing memory aids. It gives hints to the users to remember what they were thinking or what might have been their intention before shifting to the interruption task (Majaranta and Bulling, 2014). Furthermore, in previous studies, the most common highlighting method for gaze-based TRS was the last point highlighting as a placeholder (Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). Moreover, heatmap and scanpath are standard visualization methods of eye movement data to un-

[1] This Chapter is based on the following studies which are published or in work: Toreini et al. (2018c), Toreini et al. (2018b), Toreini et al. (2020a)

derstand the previous visual behavior of users. However, using these visualizations has not been investigated so far as highlighting methods for gaze-based TRS.

Following the findings from Study II, the information dashboard users also have difficulty in resuming an interrupted task, and there is a need to support them. This is considered as *MR5* in the identified MRs for designing innovative information dashboards. Also, as discussed in Chapter 1, Section 1.2 and findings from Study I, investigating how to design gaze-based TRS for information dashboards is a research gap. Therefore, I focus on closing this gap and address the first part of the fifth RQ in this thesis:

> ***RQ5a:*** *How to design attentive information dashboards providing individualized VAF to enhance users' ability to manage attentional resources in resuming interrupted tasks?*

The impact of interruptions varies and depends on individual user characteristics. Previous studies showed that user characteristics such as WMC play an essential role in managing interruptions (Cane et al., 2012; Foroughi et al., 2016; Mark et al., 2008; Ratwani and Trafton, 2008; Werner et al., 2011). Users with higher WMC can better remember their previous visual behavior and thus can better deal with task resumptions. However, as discussed in Chapter 1, Section 1.2 and the results from Study I shows that investigating the impact of gaze-based TRS under consideration of WMC is a research gap in this field. Also, as the suggested *MR6* from Study 2, the provided feedback to support users should consider the WMC of the users. Therefore, I focus on closing this gap and address the second part of the fifth RQ in this thesis:

> ***RQ5b:*** *What is the role of working memory capacity in effectiveness of gaze-based task resumption supports?*

As Figure 7.1 shows, this study focuses on the third design cycle of the DSR project. First, I review related work on designing gaze-based TRS and conceptualize it by identifying different dimensions that impact designing effective gaze-based TRS. Second, I present MRs and derive DPs for designing attentive information dashboards that support users' task resumption after interruptions. Third, I discuss the development step by presenting the system architecture and different highlighting methods suggested for gaze-based TRS. Fourth, I test the DPs in an exploratory laboratory experiment by investigating the role of WMC on the impacts of gaze-based TRS. Fifth, I present the results from the experiment and discuss different highlighting methods based on the role of WMC.

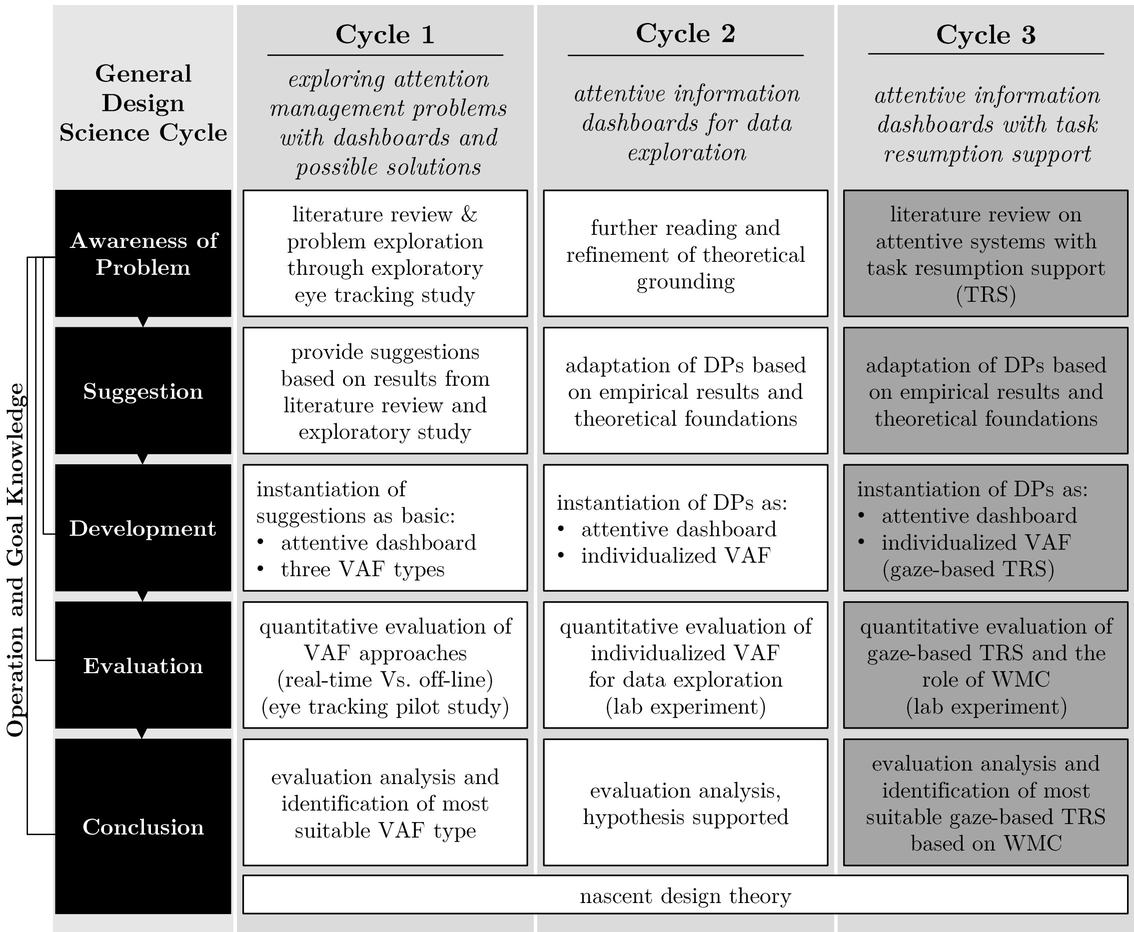


Figure 7.1.: The focus of Study V in this DSR project.

7.2. Background and Conceptualization

This section first introduces related work for TRS studies that used eye tracking technology. Furthermore, I provide a conceptualization of gaze-based TRS and investigate different dimensions that are needed to design an effective gaze-based TRS.

Gaze-based TRS and Highlighting Methods

The generic task interruption process was initially conceptualized by the *"Memory for Goals"* theory introduced by (Altmann and Trafton, 2002). Based on this theory, each task comes with a goal. When a primary task is interrupted, the goal is stored in the user's memory. After finishing the secondary task, the primary task needs to be resumed, which means the goal needs to be retrieved from the memory. This step is known to be difficult for users and takes dedicated time. A phenomenon that can be experienced in a multitasking environment is work fragmentation and difficulty in retrieving information from memory to resume tasks. Thus, the user's memory is under the competition of several goals at once and is challenged by recalling specific goals for tasks in an efficient way.

Gaze-based TRS applications use the information gained from the user's attention to assist the resumption of an interrupted task. Visual attention is inferred by an eye tracker or a camera system that records the user's eye movements and presence (Carrasco, 2011; Kowler, 2011). The examination of fixations on certain UI elements helps the system to understand how users' attention is distributed between the elements. TRS applications provide feedback that highlights certain points or areas of the previous high visual interest of the user to assist the user in resuming an interrupted task. These systems have shown to be supportive during task resumption as they decrease the resumption lag and increase the overall individual performance (Cheng et al., 2018; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015; Taylor et al., 2015).

For example, Kern et al. (2010) developed a gaze-based TRS application called Gazemarks that delivers a visual placeholder to ease attention switching between two main tasks in a multi-monitor setup. The authors of this study used last fixation point visualization as a visual placeholder. Jo et al. (2015) developed EyeBookmark in which they used eye trackers to support users recovering from the last reading position. They developed four different highlighting methods and investigated their effect on the resumption lag and the reading performance. The first highlighting method was the last fixation point visualization in which they highlighted the last read word in the text. Second, they highlighted a block that includes a fixed number of lines in addition to the last fixated word. Third, they highlighted the whole sentence in which the user was interrupted. Finally, they highlighted the previous sentence before the interruption as a reminder for the reader. In another study, Mariakakis et al. (2015) developed SwitchBack to support reading a text on mobile devices with smaller screen sizes. This TRS also guides the user back to the appropriate region by highlighting the last row of the text that was read before the external distraction. Also, Taylor et al. (2015) developed EyeFrame as a system that used the collected eye movement data in previously high-visited AOIs and drew a pale red line around them as a memory aid. Also, Cheng et al. (2018) developed Smooth Gaze in which the last fixation visualization was used as a highlighting method to support task transfer and recovery across devices when users needed to shift their attention among them.

The last fixated point highlighting method is the most common highlighting method in previously developed gaze-based TRS. Furthermore, highlighting borders of high-visited AOIs was used as a gaze-based TRS. However, the standard visualization techniques for eye tracking data such as heatmap and scanpath are not investigated so far in the context of gaze-based TRS. These common visualization techniques represent the summary of attention allocation and attention shifts of the users while visually process some information and can increase their self-awareness. Furthermore, there is a lack of research comparing these highlighting methods with each other. Comparing different highlighting methods as gaze-based support tools are tested in collaboration tasks (D'Angelo and Gergle, 2018) or online strategic games (Newn et al., 2017). To close this gap, I focus on comparing the last point, heatmap, and scanpath highlighting method for supporting task resumption in this study.

Gaze-based TRS Conceptualization

Figure 7.2 depicts the four main dimensions I identified for designing effective gaze-based TRS by analyzing existing research in the field of interruptions and gaze-based TRS. In this study, I tried to control for the task, context, and interruption characteristics and focused on different user characteristics.

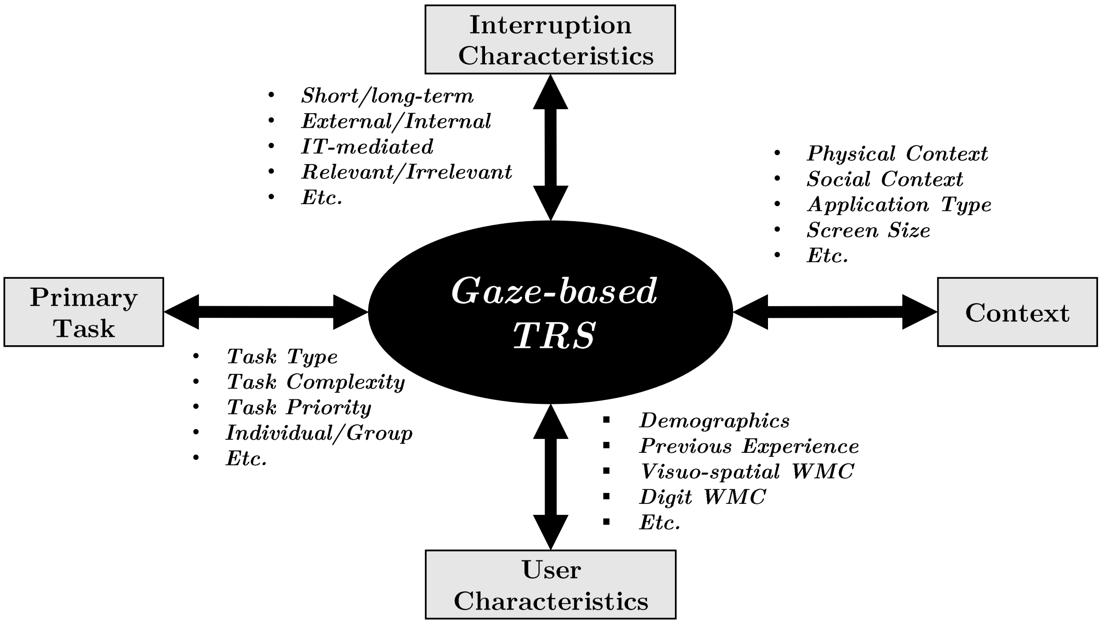


Figure 7.2.: Conceptualization of gaze-based TRS.

The first dimension of the gaze-based TRS concept is the type of primary task in which interruptions are disrupting. Previous eye tracking studies showed that the given task affects users' eye movement patterns (Yarbus, 1967). Therefore, to find the proper highlighting method for gaze-based TRS, it is necessary to know the type of task, its complexity, priority, being an individual or group task, etc. influence the design of the gaze-based TRS. In previous studies, reading tasks (Cheng et al., 2018; Jo et al., 2015; Mariakakis et al., 2015), monitoring task (Taylor et al., 2015), browsing (Kern et al., 2010) received attention by researchers. However, I believe that it is necessary to study gaze-based TRS in more diverse tasks.

Additionally, context and task are known as two elements that guide the design of any interactive system (Benyon, 2013). The environmental states are considered as the physical context. Previous studies in this field have focused on the situation in which users are working with digital applications. (Kern et al., 2010) tested a gaze-based TRS system in driving simulators and checking the navigation system, whereas (Taylor et al., 2015) used TRS in a gaming application. (Mariakakis et al., 2015) tested TRS in a mobile application, and (Cheng et al., 2018) examined their gaze-based TRS in reading applications. More contexts such as social aspects, another type of digital application, real-world interactions with augmented reality or glasses can be further options for investigation.

The third dimension is the characteristics of the interruption as a secondary task, which can be seen by interruption's source, duration, and its relevance. Generally, there are two different types of interruptions with regards to their source (Dabbish et al., 2011). First, external interruptions are triggered by events in the environment, like a phone ringing, IT-mediated interruptions such as notifications from groupware or instant messaging tools or short talks with colleagues. Second, internal interruptions are caused by internal reasons related to attentional shifts, such as thinking about vacations, shopping or past events. Besides the source, the duration of interruption also affects the task resumption. A longer and more demanding interruption leads to a slower task resumption (Monk et al., 2004,0). Also, the moment in which interruptions happens have different influences within task execution (Adamczyk and Bailey, 2004). Finally, task-relevant interruptions have been identified as an improvement of user's performance, while irrelevant interruptions are known as disruptive (Stothart et al., 2015).

The fourth dimension is the user characteristics that influence their ability to manage the interruption and resumption. Based on user characteristics, the type of gaze-based TRS might be different. User demographics such as age, gender, expertise level, and WMC are examples of user characteristics. Although previous research examined the role user characteristics on handling interruptions (Cane et al., 2012; Foroughi et al., 2016; Mark et al., 2008; Ratwani and Trafton, 2008; Werner et al., 2011), this is rarely investigated in the context of TRS. For example, user-specific reading behavior can enhance the detection of mind wandering and the reduction of internal task disruption in the process (Bixler and D'Mello, 2016). To the best of my knowledge, none of the existing studies investigated the role of individual characteristics in the context of gaze-based TRS. It is not clear if gaze-based TRS should be designed for all users in the same way or if individualized gaze-based TRS would positively impact user performance.

As an individual characteristic for this study, I emphasize WMC because of the following reasons: First, it plays a vital role in complex cognitive tasks, such as comprehension, reasoning, and problem-solving (Engle, 2002). Besides, theoretical frameworks about interruption emphasize the role of working memory in handling interruptions (Altmann and Trafton, 2002; Borst et al., 2015). Also, it has been shown that users with different WMC can handle interruptions in different ways (Cane et al., 2012; Foroughi et al., 2016; Ratwani and Trafton, 2008; Werner et al., 2011). Moreover, it is considered as an essential individual characteristic while users are working with visualized information such as on information dashboards (Haroz and Whitney, 2012; Healey and Enns, 2012; Toker et al., 2013). I focus particularly on the visuospatial WMC of the user since it reports how well the user can reproduce a sequence of locations. I assume that when users are exploring information dashboards, they read a sequence of AOIs. The ability to remember their previous exploration sequence can help them to have a better resumption performance.

7.3. Meta-requirements and Design Principles

Deriving MRs for this study is based on the **initial MR5** found in Study II. Based on that, an innovative information dashboard should support users to resume an interrupted task. In this study, I identify refined MRs for this initial MR. Furthermore, I integrate MRs provided in Study IV to design attentive information dashboards for data exploration and refined them to derived MRs for attentive information dashboards with TRS.

To ease the MRs description, I first provide an example scenario representing the steps for the interruption in Figure 7.3. In this scenario, I assume that a user works with an information dashboard and is busy with a primary task. Later, a team member opens the door and asks for a request, which results in an attention shift from the primary task to the secondary task (in this example, external interruption happens, however, other types of interruption such as IT-mediated and internal interruptions can be the case). After finishing the interruption task, the user of the information dashboard returns to the primary task. This is the moment that can get the benefit of a memory aid that supports handling the resumption performance.

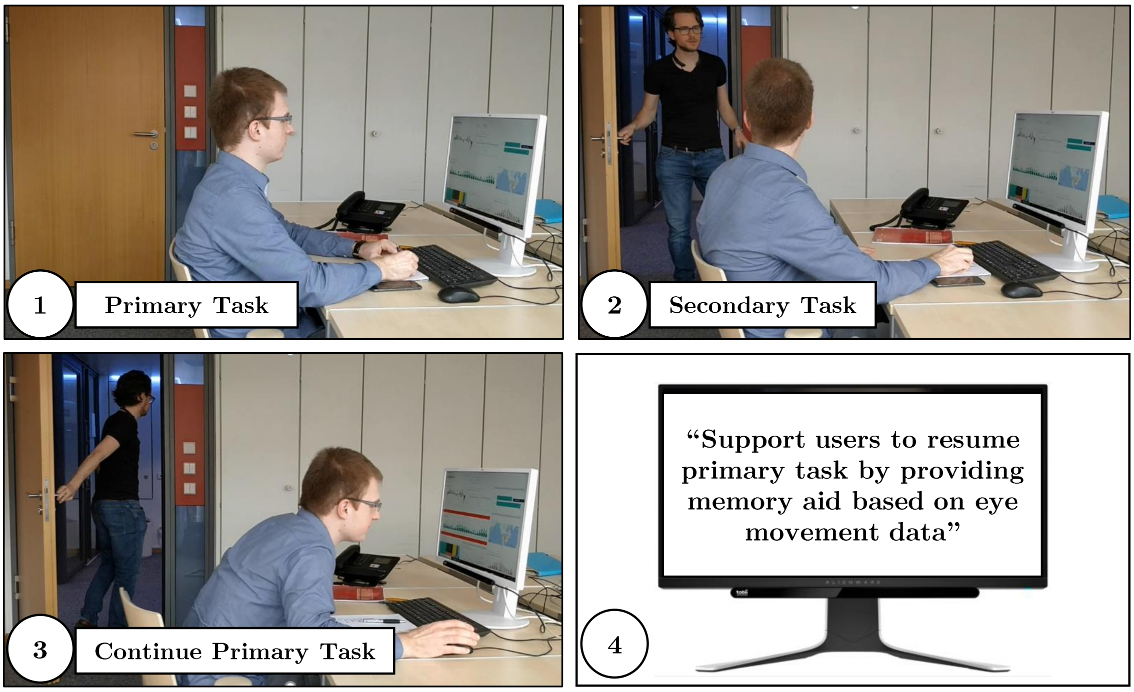


Figure 7.3.: Example scenario to represent steps for providing TRS.

Processing visualized information of information dashboards is done through visual perception. Eye movement data is known as a resource to analyze users' cognitive processes (Hayhoe and Ballard, 2005; Kowler, 2011; Liversedge and Findlay, 2000; Rayner, 1998). Furthermore, eye tracking technology is seen as the leading technology for designing attention support systems (Bulling, 2016). Therefore, as the **MR1**, attentive information dashboards should be able to track user's eye movement data in real-time while processing an information dashboard.

Nowadays, employees are often distracted by interruptions originating from different sources such as IT-mediated notifications, phone calls, or colleagues (Czerwinski et al., 2004; Mark et al., 2008). These type of interruption that has a source from external element referred to as external interruptions. Although some of those interruptions have a positive effect on the performance, some have negative effects or both (Addas and Pinsonneault, 2015). In the case of interruption, users need to shift their attention from primary to secondary tasks. Eye movements are effective in measuring the user's attention status and infer the user's intention, e.g., shift their attention (Carrasco, 2011; Hayhoe and Ballard, 2005; Liversedge and Findlay, 2000; Orquin and Mueller Loose, 2013). Therefore, as the **MR2**, attentive information dashboards should be able to estimate the user's attention based on the tracked eye movement data in real-time.

Interruptions are provoking a shift of attention from the primary task to the secondary task (Speier et al., 1999). Recognizing attention shifts due to the external interruption is essential for designing TRS (Altmann and Trafton, 2004; Roda, 2011). This recognition can be by tracking users' interaction data or users' cognitive state through external devices such as eye tracking. Therefore, as the **MR3**, attentive information dashboards should be able to recognize the occurrence of external interruptions. Furthermore, to assist the user in resuming the primary task, the end of the secondary task must be recognized. This can be identified by the start of resuming the primary task. Recognizing a resumption means that the eye tracker detects the user's eye movements upon returning to the application for the primary task (Mariakakis et al., 2015). Therefore, as the **MR4**, attentive information dashboards should be able to recognize the occurrence of task resumptions.

Studies show that interrupted primary tasks are not resumed right away (O'Conaill and Frohlich, 1995). When starting the resumption of the primary task, users tend to think again about their main goal and the amount of the task they did so far. Previous studies have shown that providing support during this recovery process helps the users' performance and reduces the resumption lag (Jo et al., 2015; Mariakakis et al., 2015). Moreover, supporting users with task interruption is known as one of the critical issues in the IS community (Addas, 2010). Therefore, as the **MR5**, attentive information dashboards should be able to support the users' recovery process. In addition to that, studies show that task resumption is primary a memory-based process (Altmann and Trafton, 2002) and some other general human cognitive, perceptual, and motor processes (Salvucci, 2010). Resuming the primary task comprises remembering to restart the interrupted task and restoring the context of the primary task (Bailey and Konstan, 2006; Cane et al., 2012). Previous studies have shown that providing gaze-based TRS by highlighting the last visual behavior is supportive for users' task resumption performance (Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). Providing gaze-based TRS gives a hint about what was in the visual interest of them before the interruption. This information is assisting users back to the relevant points again after facing the interruption. Therefore, as the **MR6**, attentive information dashboards should provide the previous visual behavior of the users as the support for the users' recovery process.

Based on the model of memory for goal (Altmann and Trafton, 2002), each task has a goal, while users need to allocate attentional resources to conduct their tasks. Furthermore, the goal is associated with the users' eye movements (Ratwani and Trafton, 2010). Attention-aware systems are known as a type of systems that support users in different phases of interruptions (Bailey and Konstan, 2006). Existing research shows that attention-aware systems assist the user by integrating the eye movement data to infer the user's visual attention before providing TRS (Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015)). As discussed, tracking the users' eye movement data and extract attentional states is needed for such a system (MR1, MR2). Therefore, I suggest the first DP **(DP1)** as providing the information dashboard with eye tracking technology to track users' attention allocation.

In order to provide TRS, there is is a need to detect the interruption as well as the resumption (MR3, MR4). Although these interruptions can have different resources, this research is focused on external interruptions and detecting attention shifts in real-time. Traditionally, mouse and keyboard actions are used to measure the interruption and resumption lag (Adamczyk and Bailey, 2004; Altmann and Trafton, 2004; Iqbal and Horvitz, 2007) or detecting strategies for task resumption (Dragunov et al., 2005). Lately, users' ability to manage the interruptions was measured with other resources such as psycho-physiological sensors (Züger and Fritz, 2015) and eye tracking technology (Cane et al., 2012). Therefore, I suggest the second DP **(DP2)** as provide the information dashboard with the ability to identify attention shifts to the secondary task and resumption of the primary task.

Moreover, the need for interfaces that aid task resumption was discussed by researchers (McFarlane and Latorella, 2002). AUIs use gaze-based TRS to assist the user after an interruption such as highlighting either by color or a spotlight the last element that the user was looking at before the interruption (Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015)). Kern et al. (2010) have stated that providing gaze-based TRS after task resumption might also be a potential benefit in standard workplaces where interruptions might be longer. Czerwinski et al. (2004) found that approaches capturing and remembering representations of tasks may be useful to assist users in switching among tasks. Therefore, based on MR5 and MR6, I suggest the third DP **(DP3)** as provide the information dashboard with gaze-based TRS in order to support users to resume their primary task.

Table 7.1 shows the summary of six identified MRs and three derived DPs for designing attentive information dashboards that support users in task resumption.

<table>
<tr><th>Design Cycle 1</th><th colspan="2">Design Cycle 3</th></tr>
<tr><th>Initial MR</th><th>Refined MRs</th><th>DPs</th></tr>
<tr><td rowspan="6">Initial MR: The information dashboard should be able to support users to select a proper revisit strategy that helps resuming the interrupted task.</td><td>Refined MR1: The information dashboard should be able to track user’s eye movement data in real-time with an eye tracking device while processing information dashboard.</td><td rowspan="2">DP1: Provide the information dashboard with eye tracking technology in order to track the user’s attention allocation.</td></tr>
<tr><td>Refined MR2: The information dashboard should be able to estimate the user’s attention based on the tracked eye movement in real-time.</td></tr>
<tr><td>Refined MR3: The information dashboard should be able to recognize the occurrence of external interruptions.</td><td rowspan="2">DP2: Provide the information dashboard with the ability to identify attention shifts to secondary task and resumption of primary task.</td></tr>
<tr><td>Refined MR4: The information dashboard should be able to recognize the occurrence of task resumptions.</td></tr>
<tr><td>Refined MR5: The information dashboard should be able to recognize the occurrence of task resumptions.</td><td rowspan="2">DP3: Provide the information dashboard with gaze-based TRS in order to support users to resume their primary task.</td></tr>
<tr><td>Refined MR6: The information dashboard should provide the previous visual behaviour of the users as the support for support the users' recovery process.</td></tr>
</table>

Table 7.1.: Summary of MRs and DPs for designing attentive information dashboards that support users’ task resumption.

7.4. Development

System Architecture

To map the DPs to design features, I propose system architecture as can be seen in Figure 7.4. This architecture includes four subsystems which are structured along with the three identified DPs discussed in the previous section.

The first subsystem is **Information Dashboard Subsystem** that involves the BI&A system and information dashboard layout. The data referring to the information dashboard is transferred to both interruption handling and attention-aware subsystems for further process. The second subsystem is **Eye Tracking Subsystem** that enables recording the eye movement data with eye tracking technology. This subsystem covers the DP1 proposed in the previous section. Later the collected eye movement data is processed, and the visual attention of the users is detected. This information is transferred to the interruption handling and attention-aware subsystems as well.

The third part is **Interruption Handling Subsystem** which represents the DP2 and includes three components. The first component, *"Dashboard Status Identifier"*, continually checks whether the information dashboard is the primary running software on the user's computer or other software is activated. In case it is not the main running software, the system considers that an it-mediated interruption happened and communicates the status to the interruption analyzer component. The IT-mediated interruption can be both relevant or irrelevant; in all cases, this is an indicator that the users shift the attention to the secondary task. The second component is the *"User Status Identifier"* that tracks the external interruption of users through eye movement data and identifying the users' presence. This component considers the moment that the user is not looking at the monitor as the occurrence of an external interruption. Both components are connected to the *"Interruption Analyzer"* component that distinguishes the start and the end of the second task. The end of the second task is assumed to be the start of the primary task.

The fourth subsystem is **Attention-aware Subsystem** that represents the DP3 and includes two components. *"Attention Analyzer"* component receives eye movement data as well as dashboard layout information and discovers the user's attentional spotlight on the dashboard. Later this information is used to generate gaze-based TRS as memory aid feature by *"Feedback Generator"* component. This component is responsible for providing the proper highlighting method as gaze-based TRS.

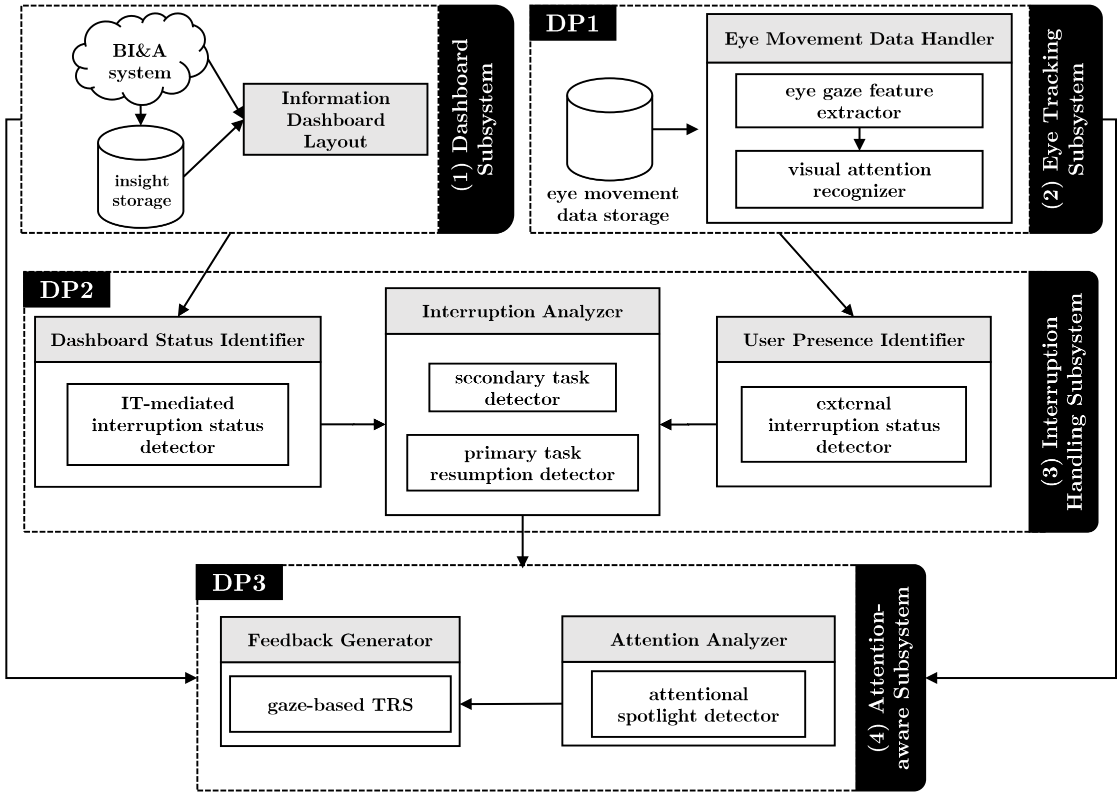
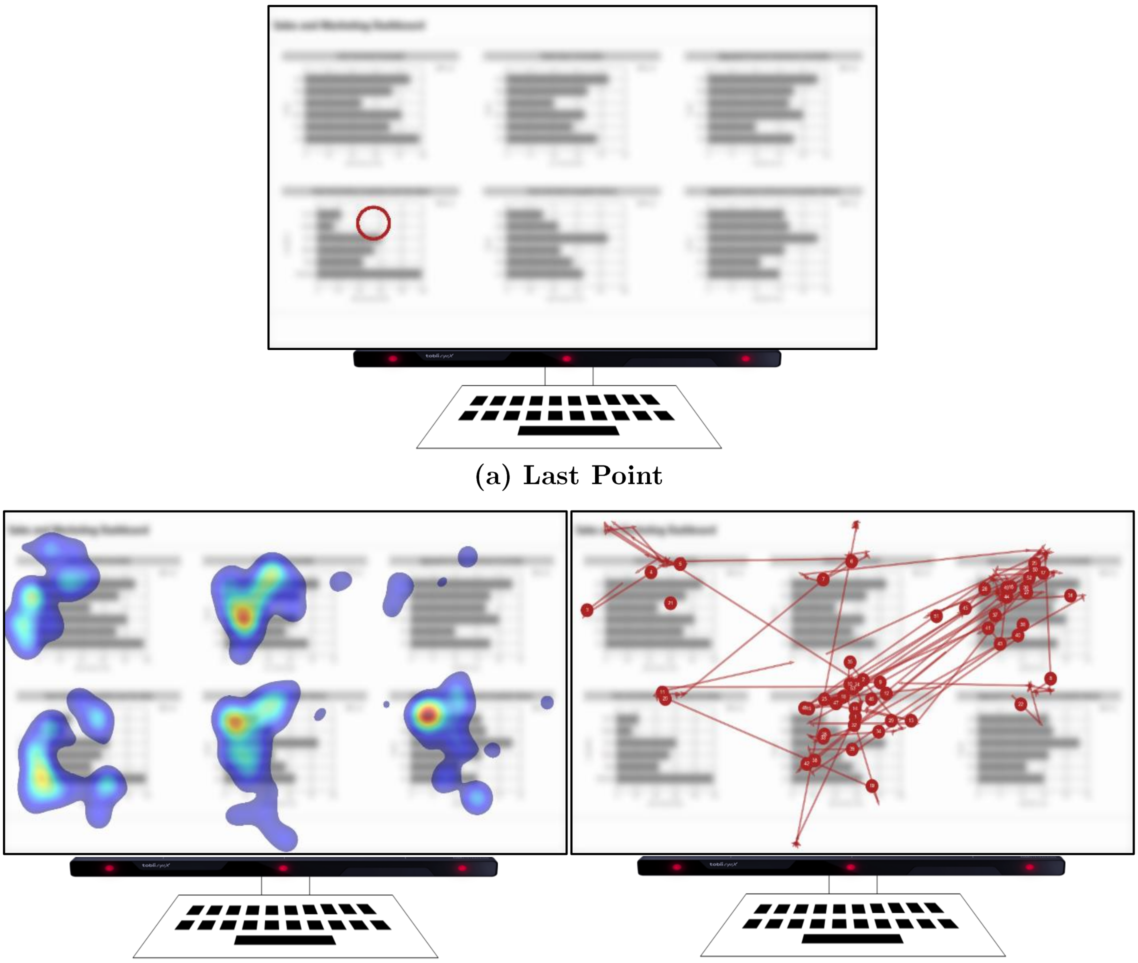


Figure 7.4.: System architecture for designing attentive information dashboards that support resuming interrupted tasks.

Highlighting Methods

I leverage three different highlighting methods, including the last point, heatmap, and scanpath in this study, as depicted in Figure 7.5. In all cases, the dashboard is blurred, and the previous visual behavior of the users is highlighted. In previous studies, the last point highlighting method is the most common method for gaze-based TRS. Besides the last point, users' attention can also be visualized with the two established eye movements visualization methods (Blascheck et al., 2014): heatmap, and scanpath. Heatmaps visualize how long a user looked at a certain point compared to the rest of the screen. Presenting such a highlighting method as gaze-based TRS can support users to recall their previous attention allocation on the AOIs and not only the last position. Moreover, the scanpath method shows the user's gaze path, including fixations on certain points of the screen. This may help perform the data exploration task on information dashboards since users need to jump between the different information pieces to get a comprehensive overview of the status quo. To extract fixations and to visualize the heatmap and scanpath, I used the PyGaze (Dalmaijer et al., 2014) as open-source toolbox. To present the last point, I used a circle shape. The center of this circle is calculated based on the mean value for the x and y of the last two fixations and the radius of 50 pixel with red color as the border.



(a) Last Point

(b) Heatmap

(c) Scanpath

Figure 7.5.: Three suggestions for DP3 as gaze-based TRS.

Information Dashboards

For this study, I designed a simple static information dashboard and control for elements that influence stimulus-driven attention, such as color-coding, size, chart type. The dashboard comprises six bar graphs, which are defined as an AOI. Furthermore, each graph has six chunks of information, and all elements are in gray. Therefore, I argue that the six AOIs of the dashboard have the same complexity regarding the design. I designed four dashboards with such design for this experiment but with changing the content of the graphs (sales, marketing, customer service, and human resource). The participants received these dashboards in random order during the experiment. An example of the dashboard design can be seen in Figure 7.6. These information dashboards with the actual content can be seen in Appendix E and Figures E.1, E.2, E.3, E.4. As discussed in Chapter 2, Section 2.2.1, this dashboard layout supports controlling stimulus-driven attention and focuses on the user's goal-directed attention. Furthermore, I focus on the overt attention of the users by tracking their eye movement data.

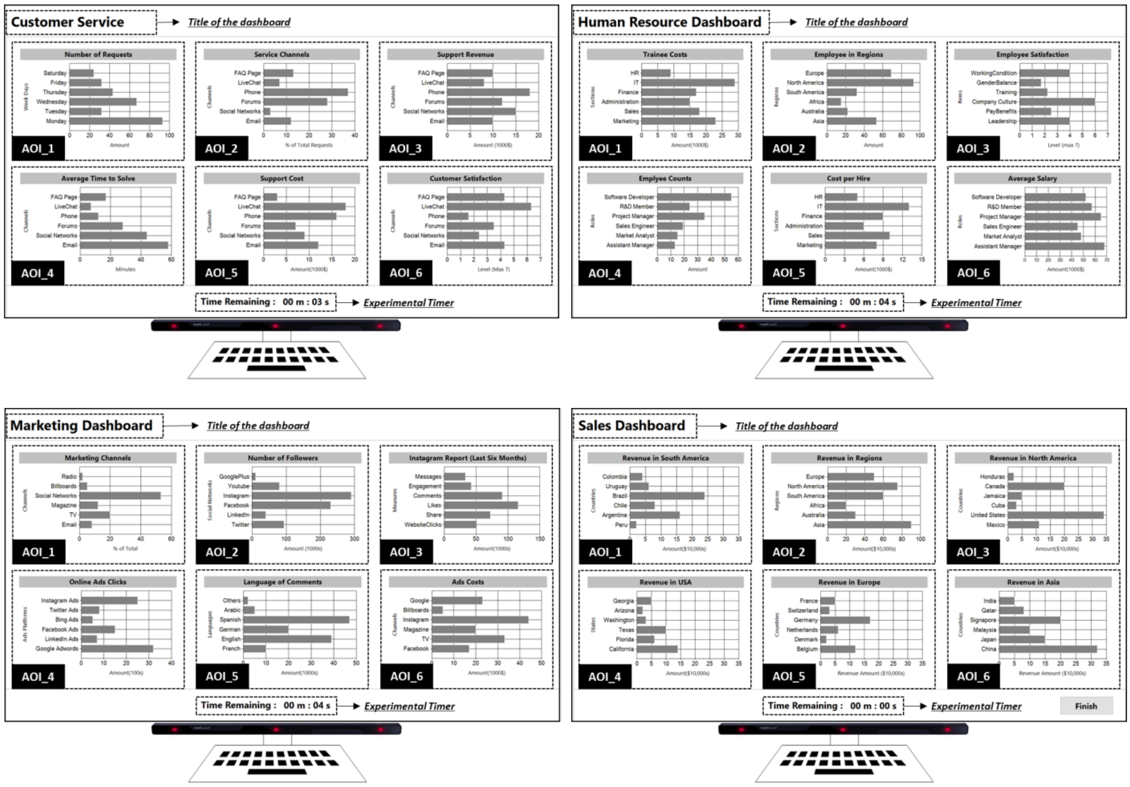


Figure 7.6.: Example of the information dashboard used in Study V.

7.5. Laboratory Experiment

7.5.1. Experimental Software and the Apparatus

Figure 7.7 shows the different stages of the task, interruption, and resumption process with the gaze-based TRS that I adapted from (Trafton et al., 2003). The first stage is the primary task that the user is diligent. The usage of visualized information in the form of an information dashboard increased these days (Yigitbasioglu and Velcu, 2012). Therefore, I picked a task on an information dashboard for this study, which was derived from the real-world workplaces. The user's task with such an application can be distinguished into search tasks and data exploration tasks (Vandenbosch and Huff, 1997). In a search task, the user tries to find information while in data exploration tasks, the user investigates all information provided on the dashboard to get a comprehensive understanding of the current status. In this study, I focus on data exploration. Also, an eye tracker records the user's eye movements to track the user's visual behavior while exploring the information dashboard. Also, to extract fixations, I used Tobii Pro SDK provided with Tobii 4C eye tracker and sensitive mode in recording fixations.

A few seconds after starting the primary task, I evoke a situation in which they face an interruption and need to shift their attention to the interrupting secondary task. In this study, the secondary task is also inspired by real-world workplaces. Here, I ask the user to answer some irrelevant emails as it-mediated interruptions. These emails are not relevant to the data exploration task and also need to be answered in a short time and do not require a long answer. Therefore, I consider them as short-term interruptions. Irrelevant and short-term interruptions are widespread and frequently happen in workplaces.

After ending the secondary task and upon resuming the primary task, the user receives one of the highlighting methods as gaze-based TRS. This gaze-based TRS presents the previously recorded eye movement data during the primary task. I assume that providing such a reminder about previous visual behavior supports users in having a better resumption performance, including a shorter resumption lag and avoiding repetitive behavior while continuing the data exploration task.

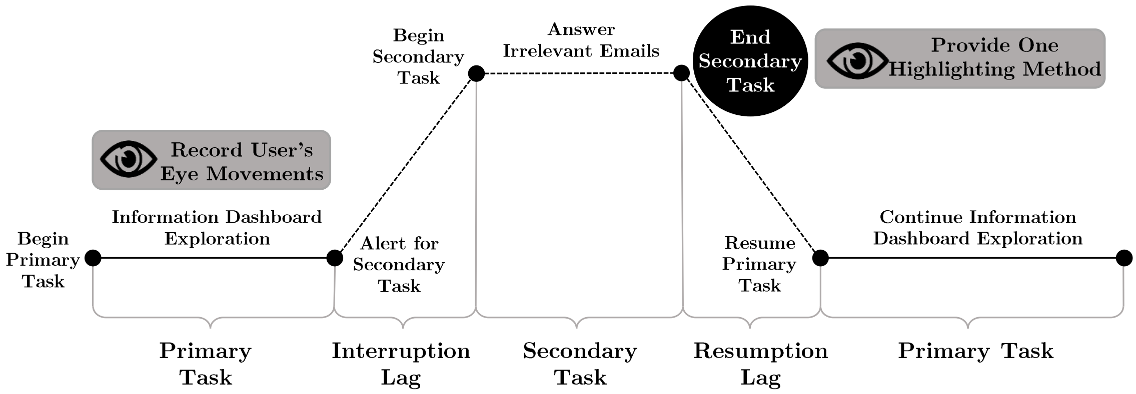


Figure 7.7.: Stages of interruption and resumption adapted from Trafton et al. (2003).

As an apparatus, I used a Tobii 4C eye tracker with a frequency of 90 Hz and the required license to record and store eye movement data for research purposes. So far, the high price of eye trackers is known as one of the obstructions to using this type of device for designing gaze-based TRS. However, Tobii 4C eye tracker is one of the low-cost eye trackers in the market (Farnsworth, 2019), and using it is in alignment with the goal of this thesis by bringing eye trackers to workplaces.

7.5.2. Experimental Design

I apply a 2×4 experimental design with users' WMC (high, low) as between-subject factors and four highlighting methods for gaze-based TRS (last point, heatmap, scanpath) as within-subject factors. I fully counterbalanced the order of the 24 unique elements, which includes the primary task (four dashboard design), interruption as the secondary task (four types of emails), and TRS condition (three gaze-based TRS and one control). To randomize this order, I prepared two boxes before the experiment and assigned 24 unique orders on each box. Before the experiment, I asked participants to draw one item of the 24 unique elements randomly, and I insert them manually into the experimental software at the beginning of the experiment. Moreover, the experimental software randomly assigned the order of the secondary tasks for each participant.

At the beginning of the experiment, I calibrated the eye tracker using the 7-point calibration with the Tobii Pro Eye Tracker Manager. The participants then received screen-based introductions, which included explanations of the provided information dashboards and the data exploration task. Later, the experimental software introduced the scenario of this experiment. The participants were asked to imagine that they just joined a fictitious company as the executive assistant to the CEO. It is their first working day at the company, and in a few minutes, they will have a meeting with the CEO and several managers to discuss the current sales, marketing, human resource, and customer service performance of the company. In order to prepare and get ready for the meeting, the task was to explore the corresponding dashboards, which they received one by one in this experiment. These dashboards can be seen in Appendix E and Figures E.1, E.2, E.3, E.4. Besides this important primary task, they had to work on other small administrative tasks in parallel and received four emails regarding their onboarding process that needed to be replied to immediately. These emails can be seen in Appendix E and in Figures E.5, E.6, E.7, E.8. The flow of the main part can be seen in Figure 7.8. These steps were repeated four times with changing dashboards and emails, which were randomly assigned to the participants.

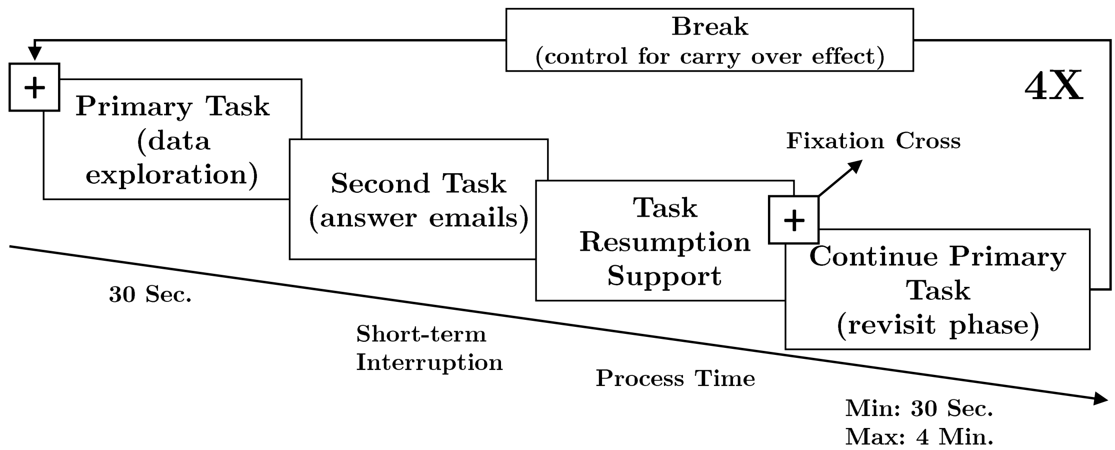


Figure 7.8.: The main steps of the experiment.

Before starting with the primary task, all users received a fixation cross on the bottom of the page outside the position of AOIs for a few seconds to control their gaze position and rest. The position for fixation cross can be seen in Appendix E in Figure E.9. As the first step, they received an information dashboard that marked the start of the primary task. After 30 seconds, the participants faced an interruption, and the secondary task phase is started. In this step, they received an email that they had to read and answer. The email was irrelevant to the data exploration task and only included some information about the onboarding process. All emails were of a similar length, and typing the answer required a similar amount of time. After sending the email, they received one of the TRS conditions. Three gaze-based TRS were designed for this experiment in addition to the without TRS condition as a control condition. In all TRS types, the users saw the TRS on top of a blurred dashboard with a similar layout. Therefore, the users did not have access to the content of the dashboard and could not continue the data exploration task while having the TRS. For the control condition, all users were forced to look at a empty screen (Appendix E Figure E.11) to wait for 10 seconds and then continued the experiment. Similar to the TRS cases, in this case, users did not have access to the dashboard content. Therefore I argue that the users in all conditions have a similar level of chance access the content of information dashboards during the experiment. After the TRS, they received a fixation cross outside the position of the six AOIs to control for the task resumption measurements. The position for the fixation cross is randomized and can be seen in Appendix E in Figure E.10.

In the revisit phase, they received the same dashboard as before the interruption to continue the data exploration. To finish the revisit phase, the participant had to press the finish button at the bottom of the dashboard. In this phase, all users were forced to explore the data for a minimum of 30 seconds and a maximum of four minutes. Therefore, the clicking function of the finish button just gets activated after 30 seconds. I chose 30 seconds as the minimum revisit period in order to have comparable time frames for the first visit and the revisit phase for all users. This procedure is repeated four times to explore the four dashboards (sales, marketing, social media, customer service, human resource).

After exploring the four dashboards, the participants answered a questionnaire about their demographics and a survey so they could rest for a few minutes. As the last step, they completed the Corsi Block-Tapping test from the PEBL software (Mueller and Piper, 2014) to measure their WMC.

7.5.3. Participants

To test the role of WMC on the gaze-based TRS, I conducted a controlled laboratory experiment. In total, 48 university students (22 female, 26 male) with an average age of 22.72 (SD=2.24) years participated. Using students fits the scenario that I examine in this study since they could imagine themselves in the defined role as a new employee in a company. Thirty-one of them did not use any visual aid during the experiment while 11 had glasses, and 6 had contact lenses as a visual aid. They received 10 Euro as compensation for their participation.

After completing the experiment, I asked the participants to rest for a few minutes, and then I analyzed their visuospatial WMC by conducting the visuospatial Corsi Block-Tapping test (Kessels et al., 2000) using PEBL test battery (Mueller and Piper, 2014). The Corsi span refers to the longest list of items that participants could memorize and repeat back in the correct order, and it is calculated by PEBL software. The higher the number of the Corsi span, the higher the visuospatial WMC. It has been seen that the average Corsi span for this test is 6 (Kessels et al., 2000). Scholars have noted that working memory span tasks are the most proper way to compare the individual's WMC with each other (Conway et al., 2005). For participants, the average WMC was 5.77 (SD=1.06). Also, the categorization of users based on their WMC used in previous studies (Lerch and Harter, 2001). To conduct the analysis, I performed a median split on visuospatial WMC to group the users based on their WMC. The median of the Corsi span for the participants was 5.75, and I assigned the users with a lower value to the low WMC group (M=4.89, SD=1.08) while I assigned users with a higher value than 5.75 to the high WMC group (M=6.64, SD=1.07).

7.5.4. Measurements

I classified the measurements in this study into four categories. The first category, control variables, focuses on the measurements used in this study to increase the quality of the results. Second, I checked the task resumption performance of the users after experiencing each gaze-based TRS. Third, I investigated how the usage of gaze-based TRS influenced task performance. Finally, I investigated the relevance of gaze-based TRS to the users by checking it from different perspectives, including user interaction data and their perception.

Control Variables: As discussed in previous sections, task, context, interruption characteristics, and user characteristics impact the effectiveness of the gaze-based TRS. I tried to control these factors in the experimental design as well as checking users' visual behavior and interactions after the experiment. In this study all the participants received the same tasks and information dashboards, they attend the experiment in the same laboratory environment with the same monitor size and resolution, all dashboards have similar visual complexity and are controlled for elements that can bias attention allocation and all participants received the same secondary tasks as an interruption. Also, users in each group have almost similar WMC as the control for user characteristics. After the experiment, I investigated the users' visual behavior in the first visit phase by checking their fixation duration among the six AOIs to ensure the similarity among users regarding the task. I also checked the secondary task period's length as an interruption based on collected log data to guarantee that users had the same interruption characteristics. Moreover, I checked if there is any difference between the dedicated time for the control condition (without TRS for ten sec.) and the processing time for the most simple gaze-based TRS, last point highlighting method.

Task Resumption Performance: I measure the resumption performance of users from four perspectives. *First*, I study the RSR by investigating the number of users in each group that could select the last AOI before interruption as the first AOI after the resumption.

I considered a minimum one-second fixation duration as the threshold for the selection of an AOI in the revisit phase. If the first AOI that the user select is the same as the last selected AOI before the interruption, I considered the users as successfully resuming. Conversely, if the first selected AOI is different from the last selected AOI, the user's resumption is considered unsuccessful. Later, I calculated the percentage of successful resumptions for each group in different conditions. *Second*, I checked the resumption lag, which is the time-period between finishing the second task and resuming the primary task (Altmann and Trafton, 2002). For that, I determined the last fixated AOI of the primary task before the interruption and calculated the time between starting the revisit phase and selecting the same last fixated AOI again. *Third*, I investigated the attention allocation performance of the users during the revisit phase. In this section, I checked their ability to ignore previously high-visited AOIs in the revisit phase. As the first visit is always 30 seconds, I calculated the attention allocation performance during the first 30 seconds of the revisit phase. For that, I checked the percentage of fixation duration on the two previously high-visited AOIs in this period. A lower fixation duration on previously high-visited AOIs during the revisit phase is considered as a higher performance in attention allocation. Fourth, I measure the centering of users' attention on a limited stimulus field by the number of transitions after resumption (Blascheck et al., 2014). I investigated the changes in the number of transitions between six AOIs before and after receiving TRS. I considered this as their ability to focus their attention on limited AOIs rather than shifting between several of them. A lower transition rate is regarded as more focused attention after the resumption.

Task Performance: As explained in the experimental design, the users could choose to finish the data exploration task after 30 seconds. I measure task performance by tracking the time that users required until clicking on the finish button as the task completion time. A faster finishing of the data exploration task is considered as better task performance.

Gaze-based TRS Relevance: This category includes four measurements that were collected via survey questions. First, I asked users about the usefulness of each gaze-based TRS with the questions adapted from Davis (1989). Second, I asked questions about how easy it was to use each of the highlighting methods as gaze-based TRS. For that, I asked questions adapted from Davis (1989). Third, I collected users' opinions about how each of those gaze-based TRS influenced their self-awareness level by asking questions adopted from Twenge et al. (2007). Fourth, I asked users about the probability that they use each of the gaze-based TRS in the future (behavioral intention) questions adapted from Venkatesh et al. (2003). List of items for each of these constructs can be seen in Appendix E in Table E.1.

Table 7.2 shows the list of measurements used in the third design cycle of the DSR project.

	Measurements	Explanation
Control Variables	**Task**	• All participants received similar task. • Visual behavior of the participants investigated by checking fixation duration among six AOIs before the secondary task.
	Context	• Lab environment, same monitor size, resolution, etc. • All participants received the same information dashboards. • All four received dashboards are visually similar. • Each information dashboard included six AOIs with the same level of complexity.
	Interruption Characteristics	• All participants received irrelevant external (it-mediated). • The length of interruption are compared with the log data.
	User Characteristics	• Users in each group have the same level of WMC.
Task Resumption Performance	**Resumption Accuracy**	• The percentage of successful resumption for each gaze-based TRS by comparing the last selected AOI before the interruption and the first selected AOI after resumption.
	Resumption Lag	• The time-period between finishing the second task and resuming the primary task based on users' fixations.
	Attentional Resource Allocation	• The percentage of fixation duration on the two previously highly visited AOIs in the revisit phase.
	Attention Shift Rate	• It represents the users' ability to focus their attention on limited AOIs rather than shifting between several of them. I compared the changes in the number of transitions between six AOIs before and after receiving gaze-based TRS.
Task Performance	**Task Completion Time**	• I measured how fast users could finish the data exploration task by checking their interaction data.
Gaze-based TRS Relevance	**Perceived Usefulness**	• User's opinion about the usefulness of each gaze-based TRS.
	Perceived Ease of Use	• User's opinion about the easiness of each gaze-based TRS.
	Self-awareness	• User's opinion about the influence of each gaze-based TRS. on self-awareness
	Behavioral Intention	• User's opinion about the probability to use each gaze-based TRS in future.

Table 7.2.: Summary of measurements used in Study V.

7.6. Data Analysis and Results

Control Variables

Figure 7.9 shows the proportion of all fixations on the six AOIs of all users during the first visit of the dashboard. Furthermore, the heatmaps of users' visual behavior in the first visit phase of the experiment can be seen in Appendix E and in Figure E.12 for low WMC users and Figure E.13 for high WMC users. As can be seen, the attention of the users from both groups is biased by the location of the AOIs for all rounds of the experiment. Users from both groups had a similar pattern and dedicated more fixations to the first and second AOI, which are located in the top-left and top-center position. Also, the low number of fixations of other AOIs highlights that users could not finish the primary task before receiving the secondary task. Therefore, this confirms that the secondary task counts as an interruption for all four conditions.

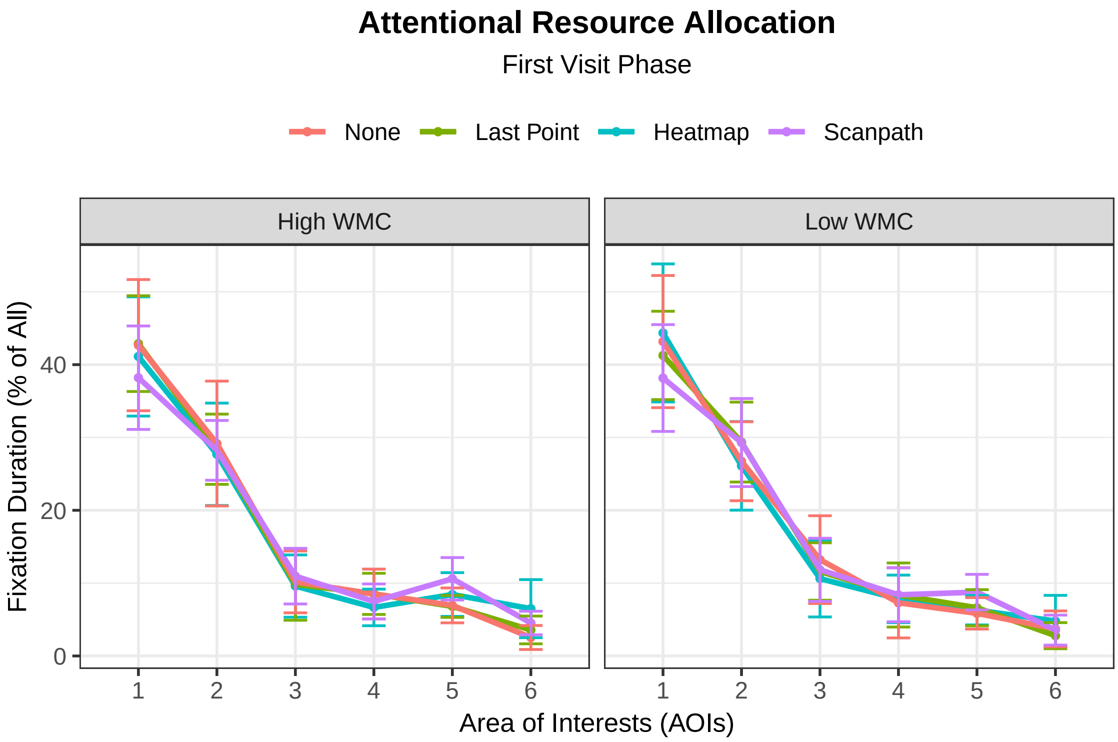


Figure 7.9.: ARA of users in the first visit phase.

In addition, I conducted a Friedman's ANOVA test revealing that the secondary task duration did not significantly differ over the four conditions, for both users with high WMC ($\chi^2(3)$=1.95, p=.58) and users with low WMC ($\chi^2(3)$=0.58, p=.89). Moreover, comparing the two groups with each other in all four conditions does not show any significant difference. Therefore, the findings show that the secondary task was similar for the users of both groups and among four conditions.

I also identified that the average process time of the last point highlighting method as the most simple method is 11.43 (SD=4.13). This processing time is close to the selected 10 seconds for the without TRS condition. Therefore, I argue that selecting 10 seconds without TRS condition was a proper decision.

7.6.1. Task Resumption Performance

Resumption Success Rate

Figure 7.10 shows the RSR. As can be seen, 58% of users with high WMC could resume their tasks successfully in the control condition while only 37% of the users with low WMC were successful. Providing the last point as gaze-based TRS also shows almost the same proportion with 54% successful users in the high WMC group and 33% in low WMC users. Nevertheless, providing heatmap shows different results. This highlighting method could support 50% of users with low WMC to successfully resume the task while only 30% of the users with high WMC were successful. Regarding the scanpath, a low amount of users in both groups (42% of high WMC, 33% of low WMC users) could successfully resume.

Overall, the results from without TRS show that both groups have difficulty in resumption (42% of the high WMC and 63% of the low WMC were not successful). Also, these findings suggest that for the high WMC group, the highest number of successful users was when I did not provide any highlighting method. None of the highlighting methods results in better performance than the baseline for this group. These findings suggest that providing these three highlighting methods as gaze-based TRS is not supportive for high WMC users. However, for the users with the low WMC, the heatmap highlighting method was supportive, and in all the other cases, they had an almost similar amount of successful users.

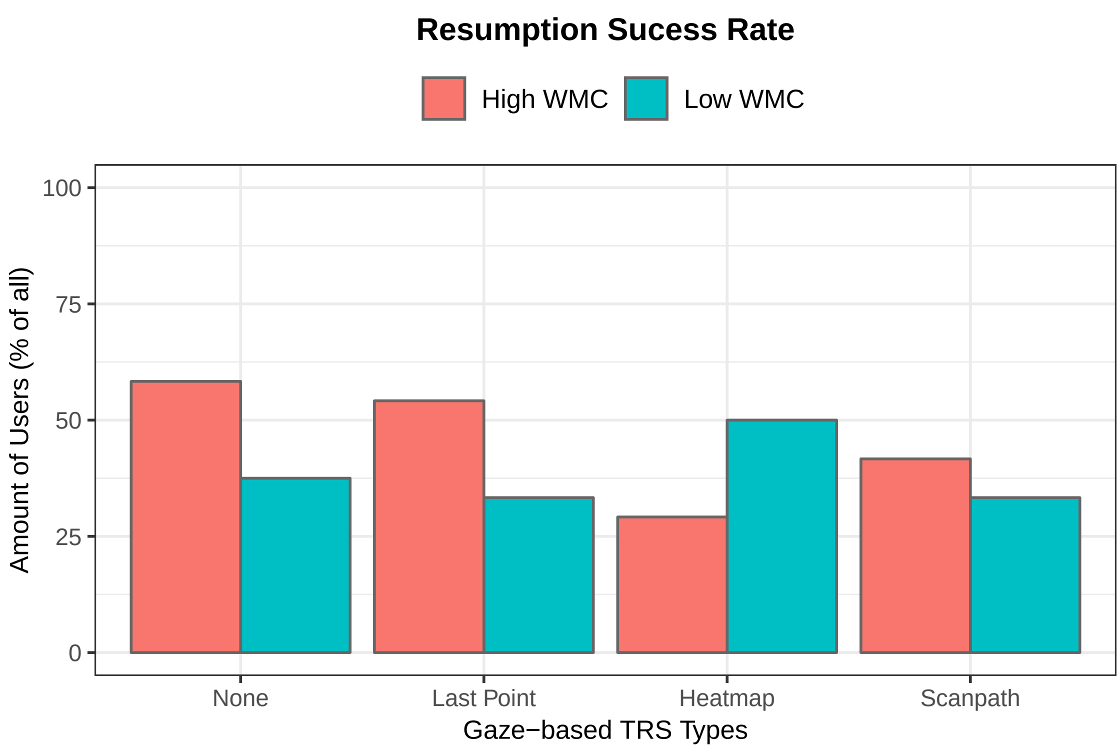


Figure 7.10.: RSR of users in the revisit phase.

Resumption Lag

Next, I checked the resumption lag as the measure of resumption performance. For the users with high WMC, Friedman's ANOVA results show that the resumption lag of participants did significantly differ over the four TRS ($\chi^2(3)$=8.1, p=.04). Post hoc tests were used with Bonferroni correction applied. It appeared that there is no difference between the without TRS condition and any other TRS condition. However, the resumption lag significantly differs from the heatmap (Mean=19.47, SD=22.69) to the last fixated point (Mean=6.74, SD=9.16) (difference=24). In all cases, the critical difference was 23.59729 (α=.05 corrected from the number of tests). For the users with low WMC, the resumption lag of participants did not significantly differ over the four conditions ($\chi^2(3)$=0.15, p=.98). Also, comparing two groups regarding their resumption lag does not show any difference.

Attentional Resource Allocation - Revisit

Figure 7.11 shows the ARA performance of both groups. To examine the difference between ARA performance, I used repeated measure ANOVA for both groups separately. First, the Mauchly test indicated that the assumption of sphericity was not violated for both the high WMC group (W=0.97, p=.98) and the low WMC group (W=0.80, P=0.43). Therefore, the results of this test are reliable for both groups.

For high WMC users, the results show a significant difference in the ARA performance among four conditions (F(3,69)=2.93, P=0.03). Post hoc comparisons using the Tukey HSD test indicated that the mean score for without TRS condition (Mean=28.20, SD=22.24) was significantly different from the last point condition (Mean=41.10, SD=17.17), (P=0.02). These findings suggest that the last point misleads users with high WMC while they had better performance without this support. The other comparisons do not show any difference. For users with low WMC, statistical results do not show significant main effects (F(3,69)=0.9, p=0.44).

Furthermore, running between analysis shows a significant main effect for WMC groups (F(3,138)=3.11, P=0.02). Executing post hoc analysis indicated that users with high WMC (M=41.10, SD=17.17) allocated more attention to previously highly attended AOIs than low WMC (M=27.02, SD=20.65) when they receive the last point as highlighting method (t(44.52)=2.56, p=.01).

As can be seen in Figure 7.11, the usage of any gaze-based TRS for users with high WMC leads to slightly higher ARA on previously high-visited AOIs (worse ARA performance) in comparison with the without TRS condition. This is the opposite for the users with low WMC while providing any gaze-based TRS supports them in a better ARA performance.

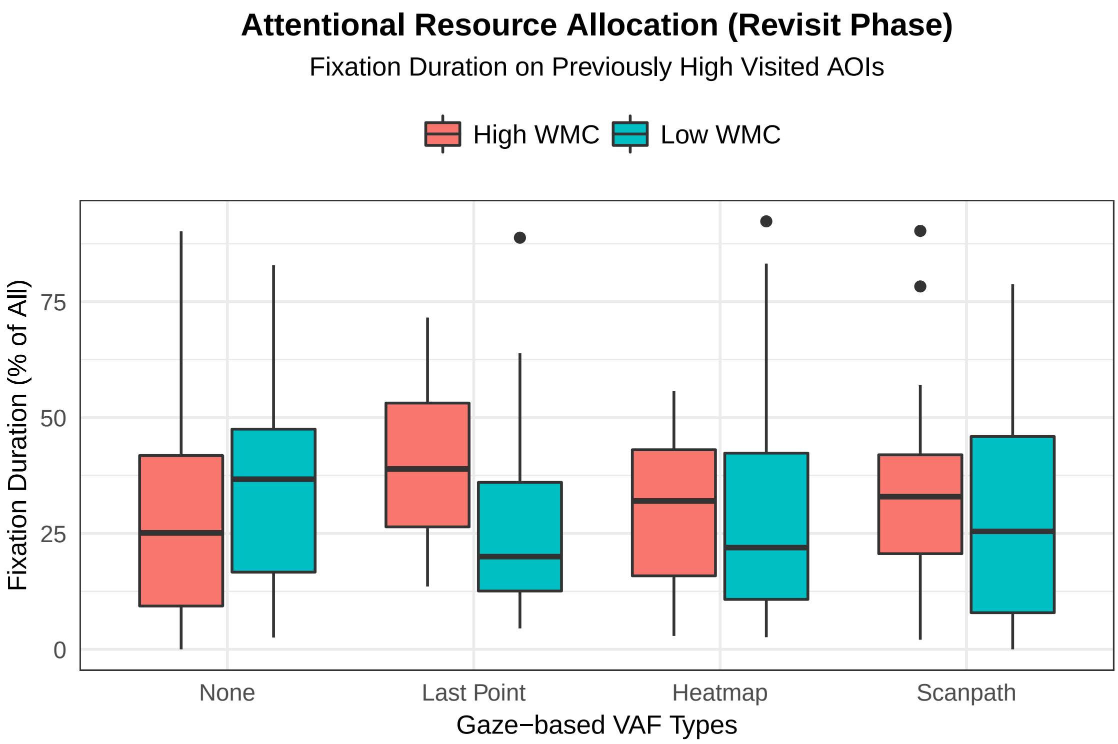


Figure 7.11.: ARA of users on previously high-visited AOIs.

Attention Shift Rate

Later, I checked the difference in the ASR in all conditions for both groups. For the users with low WMC, wilcoxon signed-rank comparison reveals that the last point highlighting leads to a significantly lower number of transitions after receiving TRS (Mean=13.46,SD=7.32) than before (Mean=16.08,SD=6.79) (Z=0.53, p=.01). For users with high WMC, the results from paired sample t-tests reveal that receiving a scanpath feedback results in less number of transitions in the revisit phase (Mean=13.83, SD=5.98) compared to the first visit phase (Mean=18.33, SD=8.53) (t(23)=2.85, p=.009). In all the other conditions, there is no difference in the ASR for both groups.

7.6.2. Task Performance

Task completion time refers to the time that users required to end exploring the information dashboard by clicking on the finish button as a part of the revisit phase. The results from Friedman's ANOVA reveal that the task completion time did not significantly differ over the four conditions, for both users with high WMC ($\chi^2(3)$=2.55, p=.46) and with low WMC ($\chi^2(3)$=2.65, p=.44). Moreover, comparing two groups with each other in all four conditions does not show any significant difference. Therefore, these findings suggest that the three highlighting methods as gaze-based TRS do not support finishing the task faster for any user group.

7.6.3. Gaze-based TRS Relevance

Figure 7.12 shows the opinions of participants from both groups regarding the perceived usefulness, ease of use, self-awareness, and behavioral intention for the three presented highlighting methods.

Perceived Usefulness

In general, users with low WMC tend to rate all highlighting methods more useful in comparison with users with high WMC. This indicates that users with high WMC are more confident in managing short-term interruptions. Comparing the perceived usefulness within each WMC group does not show any difference between the three highlighting methods. Nevertheless, comparing both groups with each other running independent t-tests shows that there was a significant effect for heatmap ($t(45.96)=-2.0886$, $p=.04$) and low WMC ($M=5.15$, $SD=1.44$) attaining higher scores than high WMC ($M=4.29$, $SD=1.4$). These results show that low WMC users found heatmap more useful than users with high WMC.

Perceived Ease of Use

Regarding the ease of use, the results from the wilcoxon signed-rank comparison show that users with high WMC found heatmap (Mean=5.57, SD=1.22) easier to use than the scanpath (Mean=4.64, SD=1.18) ($Z=0.60$, $p=.007$). The same applies for users with low WMC, heatmap (Mean=5.60, SD=0.98), scanpath (Mean=4.68, SD=1.61) ($Z=0.59$, $p=.008$). Also, there is no difference between the last point and heatmap for users in both groups.

Self-awareness

Participants from both groups believe that the scanpath and heatmap increase their self-awareness more than the last point. For users with high WMC, wilcoxon signed-rank comparison for each pair reveals that they found to be significantly less self-aware with the last point highlighting (Mean=2.24, SD=1.08) than with the heatmap (Mean=4.75, SD=1.30) ($Z=0.91$, $p<.0001$) and the scanpath (Mean=4.58, SD=1.33) ($Z=0.88$, $p<.0001$). For users with low WMC, the same test shows that they have a similar opinion. The last point highlighting (Mean=2.97,SD=1.75) lead to a significantly lower self-awareness than the heatmap (Mean=5.04,SD=1.47) ($Z=0.79$, $p=.0003$) and the scanpath (Mean=4.99,SD=1.55) ($Z=0.68$, $p=.002$). Conducting a between-subject analysis depicts that there is no difference between groups.

Behavioral Intention to Use

Regarding the behavioral intention to use, conducting a paired sample t-test for the users with low WMC shows that they prefer to use heatmap (Mean=4.31, SD=1.73) more than the scanpath (Mean=3.47, SD=1.74) ($t(23)=2.11$,$p=0.04$). There is no difference between using the last point and heatmap. For users with high WMC, there is no difference between the three highlighting methods. Moreover, users with low WMC tend to use these highlighting methods in the future more than high WMC users. By comparing the user groups, these findings suggest that especially users with low WMC have a higher intention to use heatmap than users with high WMC (t(45.54)=-2.24,p=0.02).

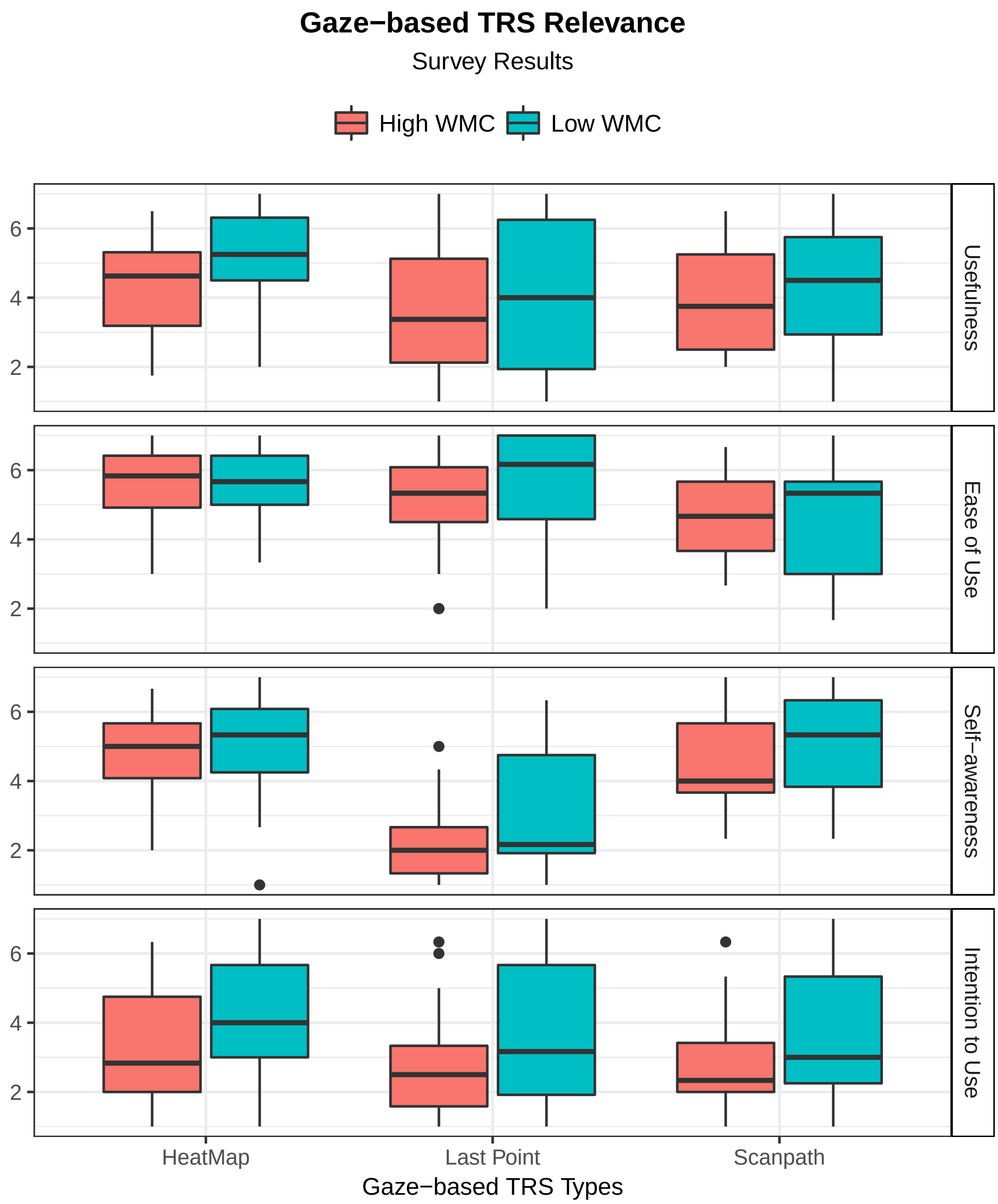


Figure 7.12.: Users' opinions about Gaze-based TRS.

7.7. Discussion

Table 7.3 shows a summary of the results collected in this study. Comparing the results indicates the importance of considering WMC when designing gaze-based TRS.

Using the last point method, the participants from both groups were not influenced strongly. However, it is a popular highlighting method in the field of gaze-based TRS. Providing this could only affect users with low WMC to have fewer attention shifts. I believe that providing a new task and interface (data exploration on information dashboards) is the primary reason for that. This finding shows the importance of designing different gaze-based TRS based on the dimensions that discussed in Section 7.2 and challenges to generalizing one highlighting method. By considering the role of WMC, I also uncovered that participants with different WMC found using the last point method easy to use, but they do not have a strong intention to use it in the future in comparison with the other gaze-based TRS types. Therefore, these findings suggest that providing last point gaze-based TRS in the specific case as performing data exploration tasks in information dashboards with short-term interruptions is not helpful for any of the user groups.

These findings show that the heatmap method is effective for participants with lower WMC, while it is not that useful for users with high WMC. For users with low WMC, this supports better task resumption performance by supporting to improve the success rate and a slightly better revisit attention allocation. Moreover, participants perceived it useful, easy to use, and supportive with regards to self-awareness. They also have a high intend to use it in the future. For users with higher WMC, this highlighting method does not support resumption performance. Besides, they have a lower intention to use in comparison with users with low WMC, although it is easy to use and can support increasing self-awareness.

Regarding the scanpath highlighting method, these findings suggest that it was supportive for users with high WMC to reduce their attention shifts and also to increase their self-awareness. However, they perceived it as not easy to use in comparison with the other gaze-based TRS types. For the participants with lower WMC, this TRS type could only positively influence the self-awareness in comparison with the last point TRS and does not have any other consequences.

Overall, these findings suggest that providing gaze-based TRS for short term interruptions is more supportive for users with low WMC than high WMC. Providing any of those highlighting methods could not play an extensive supportive role for users with high WMC. However, users with low WMC could get the benefit of them from different aspects, especially using the heatmap highlighting method.

	Measurements	Results
Task Resumption Performance	Resumption Success Rate	• For high WMC users, the no TRS condition lead to a higher resumption success rate. • For the low WMC users, heatmap condition lead to a higher resumption success rate. • For both groups, providing the last point highlighting is almost like the without TRS condition.
	Resumption Lag	• For high WMC users, providing the heatmap results in higher resumption lag in comparison with the last point. • For low WMC users, there is no difference between conditions. • For both groups, providing any gaze-based TSR does not support reducing the resumption lag in comparison with the without TRS condition.
	Attentional Resource Allocation	• For high WMC users, providing any gaze-based TRS, tends to decrease attention allocation performance. Especially the last point highlighting method has a strong effect on decreasing performance. • For low WMC users, providing any gaze-based TRS, tends to support improving attention allocation performance.
	Attention Shift Rate	• For high WMC users, scanpath highlighting supports improving focused attention. • For low WMC users, last point highlighting supports improving higher focused attention.
Task Performance	Task Completion Time	• For both groups, providing any gaze-based TRS does not improve task completion time.
Gaze-based TRS Relevance	Perceived Usefulness	• Users with low WMC perceive the heatmap more useful than high WMC users.
	Ease of Use	• For high WMC users, using heatmap is easier than scanpath. • For low WMC users, using heatmap is easier than scanpath. • For both groups, there is no difference between last point and heatmap regarding ease of use.
	Self-awareness	• For both groups, users believe that heatmap and scanpath increase their self-awareness more than the last point highlighting method.
	Behavioral Intention	• For low WMC users, the intention to use heatmaps is higher than scanpath. • For high WMC users, there is no difference between the intention to use of any highlighting method in the future. • Users with low WMC have a higher intention to use heatmap compared with the users with high WMC.

Table 7.3.: Summary of findings by comparing gaze-based TRS and the role of WMC.

7.8. Summary

The third design cycle is focused on supporting information dashboard users in resuming an interrupted task. This was identified as one of the MRs in the Study II. These days, interruptions are a crucial phenomenon in private and professional life and users are getting used to shift their attention to secondary tasks while working on a primary one frequently. The increased amount of such situations highlights the need for TRS systems. Eye tracking is a promising technology to provide TRS using gaze-based highlighting methods. With such support, users can be reminded of their previous visual behavior and assisted in resuming the primary task more efficiently in case of interruptions. In this study, I first conceptualized individualized VAF for TRS after an interruption as gaze-based TRS. Later, I presented dimensions that impact designing effective gaze-based TRS by analyzing previous research in the field of interruption and gaze-based TRS. Especially, I analyzed the collected papers in the Study I that focused on providing TRS with real-time eye movement data. Based on that, I present MRs and DPs for designing attentive information dashboards with gaze-based TRS as an individualized VAF. Furthermore, I proposed the system architecture for the development part and mapped identified DPs to the design features. For gaze-based TRS I suggested and developed three types of highlighting methods for gaze-based TRS as last point, heatmap and scanpath. Based on Gregor (2006), the presented MRs, DPs, and design features are considered as type V theory (Design and Action), since it gives explicit prescriptions for constructing attentive information dashboards that provide gaze-based TRS.

Also, the results from Study II show the need for individualization of attention support based on users working memory. By analyzing the existing research in gaze-based TRS, I identified that it is not well understood how individuals' WMC influences gaze-based TRS effectiveness. Therefore, I designed an exploratory laboratory experiment to evaluate three gaze-based highlighting methods (last point, heatmap, scanpath) after a short term IT-mediated interruption of a data exploration task. The results suggest that designing gaze-based TRS should be different for users based on their WMC. Especially heatmap, is supportive for low WMC users, while users with high WMC may not need gaze-based TRS. With this study, I provide evidence for the necessity of designing personalized gaze-based TRS considering WMC in the future. Based on Gregor (2006), the results from this exploratory study are a type II theory (Explanation), since it provides explanations about the effects of providing different gaze-based TRS after a short-term interruption.

This study contributes to the field of gaze-based TRS from different perspectives. First, I extended the current study in the field of gaze-based TRS by testing new highlighting methods, including heatmap and scanpath, and compared them with the last point highlighting as a common gaze-based TRS. Second, I extended the research field by considering a new task. To the best of my knowledge, it is the first study that investigates TRS in the context of data exploration tasks using information dashboards. This specific task is expected to influence the effectiveness of gaze-based TRS since the user's eye movement patterns depend on the context and the task. Third, I investigated the role of the user's WMC on the effectiveness of different highlighting methods.

8. Discussion [1]

8.1. Theoretical Contributions

To classify the theoretical contributions of this thesis, I rely on the taxonomy of theory types in IS research provided by Gregor (2006). Table 8.1 presents an overview of the theoretical contributions of each study.

In **Study I**, I presented a conceptualization for the systems that integrate real-time usage of eye movement data to develop innovative interaction, considered as eye-based IIS (see Section 3.2.2, Figure 3.1). Although the development of such systems increased during the last years (Chuang et al., 2019; Nakano et al., 2016), there is a lack of conceptualization for designing such systems. In an attempt to do so, I investigated to provide a conceptual framework for research on eye-based IIS. Based on Gregor (2006), this framework is a type I theory (Analysis) since it describes eye-based IIS and analyses the relationship between different dimensions of research within designing such systems. In this framework, I distinguish three high-level categories as 1) influencing factors, 2) eye-based IIS properties, and 3) outcomes. Each category involves several particular elements. The influencing factor category focuses on elements that impact the design of the eye-based IIS. This category covers context, task, eye tracking technology, experimental setup. The second category, eye-based IIS properties, is considered as the core of the framework. It includes sensing and reasoning as the fundamental elements to design eye-based IIS. Later, these properties are used to design eye-based IIS, which can have two main focuses: making the system more intelligent (system adaptation) or increasing user awareness (user adaptation). In the last category (outcome), I investigate the outcomes of the designed eye-based IIS through three dimensions: perception, behavior, and performance. Furthermore, there is a lack of an overview of existing research on the systems that integrate real-time eye movement data for designing innovative interactions. Therefore, I conducted a SLR study and developed a conceptual framework by analyzing the collected papers. Consequently, I presented a descriptive analysis based on all elements of the framework in detail. These findings reveal several potential future research directions for each dimension that guide academic researchers for further investigation of eye-based IIS.

In **Study II**, I used eye tracking technology for diagnostic purposes and conducted an exploratory study to investigate the visual behavior of users with high and low WMC while exploring information dashboards. The results from the eye movement analysis reveal that both groups of users with low and high WMC have difficulties in managing limited attentional resources while exploring information dashboards. Also, the results show that users have difficulty in resuming an interrupted task. Furthermore, in the case of a second chance to improve information processing performance, both groups of users have

[1] This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini et al. (2018c), Toreini et al. (2018b), Toreini et al. (2018a), Hummel et al. (2018), Toreini and Langner (2019), Toreini et al. (2020b), Langner et al. (2020), Toreini et al. (2020c), Toreini and Maedche (2020), Toreini et al. (2020a)

difficulty selecting a proper revisit strategy and repeat their behavior. Based on Gregor (2006), the results from this exploratory study represent a type II theory (Explanation) since it provides explanations about managing limited attentional resources of users with high and low WMC while exploring information dashboards. The findings from this study highlight the need for designing an innovative information dashboard that considers the limitations of attentional resources and WMC of the users. Therefore, I extracted six MRs for designing attentive information dashboards. Based on the developed framework in Study I, three MRs focus on designing an attentive information dashboard that reflects system adaptation focus, and the other three focus on user adaptation by increasing users' awareness with providing VAF. Following Gregor (2006), the presented MRs are considered as type V theory (Design and Action), since they provide explicit prescriptions (MRs) for constructing attentive information dashboards.

In **Study III**, I investigated different attention support solutions for information dashboard users. First, I presented three suggestions for designing VAF for the information dashboard users by integrating real-time and off-line records of eye movement data. Later, I investigated the effects of these three VAF types in an eye tracking pilot study. The first suggestion is an individualized VAF that functions by tracking the users' eye movement data in real-time and presents the users' gaze duration on each chart of the dashboard. The second VAF suggestion is a general VAF, which is an example of a proper visual attention allocation based on off-line records of eye movement data of other users who conducted the same data exploration task on the same dashboard. The third VAF type is another general VAF that follows the same approach as the second VAF but presents an example of improper VAA using off-line eye movement data. The results from comparing these three VAF types reveal that providing individualized VAF assists users in managing their limited attentional resources in a better way in comparison with providing off-line records of eye movement data as VAF (proper or improper example of visual attention allocation as VAF types). Based on Gregor (2006), the results from this eye tracking pilot study is a type II theory (Explanation), since they provide explanations about the effects of using real-time and off-line records of eye movement data as VAF on managing limited attentional resources while exploring information dashboards.

In **Study IV**, I investigated the design of attentive information dashboards for data exploration. For that, I presented two theoretically grounded DPs for designing attentive information dashboards that support the data exploration task with individualized VAF. vom Brocke et al. (2013) have emphasized that there are limited contributions in the DSR community that make actual use of the potential of neuroscience tools (e.g., eye tracker) to design advanced built-in functions for IT artifacts. Eye tracking technology has recently been extended in IS research (Dimoka et al., 2012; Riedl et al., 2017); however, the usage of it was limited to analyzing off-line eye movement data to understand human visual activities while working with IS applications (Riedl et al., 2017; Vasseur et al., 2019). In this study, I contribute to the field of IS by integrating real-time eye movement data to support users in managing their limited attentional resources while exploring information dashboards. Furthermore, I presented a system architecture for attentive information dashboards that support data exploration with three components. This system architecture promotes mapping two provided DPs to design features. Based on Gregor (2006), this contribution is considered as type V theory (Design and Action), since it gives explicit prescriptions for constructing attentive information dashboards that provide individualized VAF for data exploration tasks. Later, I instantiated both DPs in a software artifact and evaluated them in a large-scale laboratory experiment as a suggested method to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012). In this experiment, I compared two design configurations with DPs activated (individualized VAF) and deactivated (general VAF with a text-based explanation about attention). For the evaluation, I suggested an underlying research model and three hypotheses examine the impact of the proposed DPs. For the data analysis, I focused on collected eye movement data during the experiment. I mainly analyzed users' eye movement data while exploring the information dashboard in the first visit, after receiving the individualized VAF (revisit phase) and at the end of the task. The results of this study reveal that individualized VAF enhances users' ability to manage limited attentional resources. Based on the findings, the users without DPs had difficulty in managing their limited attention from different perspectives (Attentional Resource Allocation, Attention Shift Rate, and Attentional Resource Management) while users with DPs performed better in all perspectives. Based on Gregor (2006), this contribution is considered as II theory (Explanation) since it provides explanations about the effects of using DPs on enhancing users ability to manage their limited attentional resource during data exploration tasks.

In **Study V**, I first conceptualized individualized VAF that supports resuming interrupted tasks, gaze-based TRS. Later, I presented dimensions that impact designing effective gaze-based TRS by analyzing previous research in the field of interruption and gaze-based TRS. The detailed conceptualization is discussed in Section 7.2. Based on that, I presented six MRs and three DPs for designing an attentive information dashboard that supports users' task resumption with gaze-based TRS. Next, I proposed the system architecture for developing such systems. This system architecture helps to map three identified DPs to the design features. Also, for this study, I suggest three types of highlighting methods for gaze-based TRS as last point, heatmap, scanpath. Based on Gregor (2006), the presented MRs, DPs, and design features are considered as type V theory (Design and Action), since it gives explicit prescriptions for constructing attentive information dashboards that provide gaze-based TRS. Furthermore, this study extends the current knowledge in the field of gaze-based TRS by integrating new highlighting methods (heatmap and scanpath) for gaze-based TRS. Based on the collected papers in the Study I, the previous studies focused mainly on last point highlighting methods, and the comparison of different highlighting methods was not investigated. This study also extends the gaze-based TRS research field by considering a new context and task by using information dashboards for data exploration tasks. Later, I investigated the role of the user's WMC on the effectiveness of different highlighting methods for short term IT-mediated interruptions in a large-scale exploratory study as a suggested method to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012). The results suggest that the need for gaze-based TRS types is different for users with high and low WMC. Notably, the heatmap highlighting method is supportive for low WMC users, while users with high WMC may not need gaze-based TRS for short-term IT-mediated interruptions. Based on Gregor (2006), the results from this exploratory study are a type II theory (Explanation), since it provides explanations about the effects of providing different gaze-based TRS after a short-term interruption.

	Study	Theory Type	Main Contributions
SLR	**I**	Type I theory: Analysis	• Conceptualization of eye-based IIS along with the three high-level categories: influencing factors, eye-based IIS properties, outcomes. • Descriptive analysis of research on using real-time eye movement data for designing eye-based IIS. • Formulation of future research directions for eye-based IIS.
Design Cycle 1	**II**	Type II theory: Explanation	• Users with high and low WMC have difficulty in managing limited attentional resources while exploring information dashboards.
		Type V theory: Design and Action	• Formulation of MRs for designing attentive information dashboards that focus on making the system more intelligent and support system adaptation or increasing user awareness and support user adaptation.
	III	Type II theory: Explanation	• Provide suggestions as VAF types (utilizing real-time or off-line records of eye movement data). • Individualized VAF (utilizing eye movement data in real-time) supports managing limited attentional resources in a better way compared with the proper and improper examples of attention allocation as VAF types (utilizing off-line records of eye movement data).
Design Cycle 2	**IV**	Type V theory: Design and Action	• Formulation of MRs, DPs, and DFs for designing an attentive information dashboard that supports data exploration tasks with individualized VAF.
		Type II theory: Explanation	• Individualized VAF support users in managing their limited attentional resources during data exploration tasks.
Design Cycle 3	**V**	Type V theory: Design and Action	• Formulation of MRs, DPs, and DFs for designing an attentive information dashboard that supports task resumption after an interruption with gaze-based TRS.
		Type II theory: Explanation	• Users with different WMC, need different types of highlighting methods as gaze-based TRS.

Table 8.1.: Theoretical contributions according to theory types by Gregor (2006).

8.2. Practical Contributions

The results of this thesis also are beneficial for at least two groups of practitioners. The first group is information dashboard designers who concentrate on designing information dashboards for existing BI&A platforms. The second group comprises eye-based application designers who are mainly HCI practitioners that focus on integrating real-time eye movement data for designing innovative interactions in different contexts and tasks.

Information Dashboard Designers

Designing effective systems requires a detailed understanding of the underlying cognitive processes while users working with them (Lerch and Harter, 2001). The results from the Study II support information dashboard designers to better understand the role of limited attentional resources and working memory while users explore information dashboards. Researchers have used eye trackers to evaluate some specific design features on information dashboards (e.g., presentation formats, colors, size, position, etc.) (Alberts, 2017; Bera, 2014,1; Burch et al., 2011; Nadj et al., 2020) and limited attention and working memory challenges of information dashboard users are not investigated. For instance, dashboard designers need to highlight critical business states in their design since users have difficulty managing their attentional resources and may miss some information. Previous studies have addressed the need for providing such feedback to inform users about critical business states proactively (O'Donnell and David, 2000; Yigitbasioglu and Velcu, 2012). They can also consider designing personalized information dashboards based on users' WMC or their ability to manage limited attentional resources. Furthermore, users' visual behavior in Study I, and control groups of Study IV and Study V show that users repeat their visual behavior in the revisit phase. This happens since they have difficulty to remember those activities which have been completed (Singh, 1998). This can result in missing changed information on dynamic dashboards (Healey and Enns, 2012). Therefore, information dashboard designers should consider highlighting changes when users revisit information dashboards to avoid missing important information.

So far, commercial BI&A tool providers, such as Tableau, use eye trackers for understanding user's behavior while exploring dashboards (Alberts, 2017). But, the usage of eye movement data in real-time for creating attentive information dashboards is not yet integrated into BI&A platforms (Silva et al., 2019). Within the last years, technology firms have recognized the potential of neuroscience technologies in advancing user and IS applications (vom Brocke et al., 2013). So far, the high price and complexity of neuroscience tools challenged using these devices in workplaces. However, the usage of eye tracking technology increased in recent years because of the availability of cheaper, faster, more accurate, and easier to use eye trackers (Duchowski, 2017). In this DSR project, I used the Tobii 4C eye tracker [2] as one of the cheapest eye trackers in the market (Farnsworth, 2019) to develop attentive information dashboards with two types of individualized VAF. This DSR project provides prescriptive knowledge that guides the design of attentive information dashboards for practice (Gregor and Hevner, 2013; Peffers et al., 2007). Particularly the

[2] https://gaming.tobii.com/tobii-eye-tracker-4c/

presented information in Study IV and V can support commercial BI&A tool providers to enhance their capabilities by designing attentive information dashboards with eye trackers. They can replicate the design of individualized VAF for data exploration tasks or provide support for resuming interrupted tasks. Also, they can use the attentive information dashboard to design further individualized VAF that supports other tasks. For example, they can integrate attentive information dashboards in collaborative scenarios and enhance the team's joint attention with individualized VAF (Toreini et al., 2018a).

Eye-based Application Designers

The usage of eye trackers has moved from the controlled lab environment to everyday settings (Chuang et al., 2019). The number of applications that work with eye tracking increased during the last years. Tobii company as one of the leading companies in this field has announced that eye tracking technology is coming to the devices we use every day and enterprises should get ready for that (Eskilsson, 2019). Besides, Microsoft recently released the usage of eye control on Windows 10 to ease the interaction between users and the system (Microsoft, 2019). This thesis's findings can support eye-based application designers to design new eye-based features. The results from the Study I can support eye-based application designers to understand different dimensions of integrating real-time eye movement data for designing innovative IIS. Also, it provides a comprehensive overview of existing research studies in this field from different perspectives. Furthermore, the results from Study III and Study IV support eye-based application designers for designing data exploration support features for enterprise applications beyond information dashboards. For example, SAP considered the usage of eye trackers for the next version of enterprise systems (Galer, 2019), and such feedback can be integrated into other enterprise applications that users need proper attention allocation. Also, it can be integrated into self-tracking dashboards in workplaces such as MyAnalytics dashboard [3] developed by Microsoft and support them to manage their limited attentional resources. The results from the Study V can be integrated into applications and tasks that users need for several attentional shifts. For example, such feedback can be for the employees that need to work on several monitors or to work in situations with high interruption rates.

Furthermore, the developed attentive information dashboards and individualized VAF types can be transferred for the situations that need to wear head-mounted eye trackers. For example, the results from the Study III and Study IV can be integrated into google glass enterprise edition (Kothari, 2019) to help business employees to work smarter by managing their attentional resources while exploring information in real-world. In another example, the results from this DSR project, especially the Study III, IV, and V can be integrated into the VR scenarios. Eye tracking technology enables new forms of interactions in VR and AR, and the suggested individualized VAF in this DSR project can be integrated into VR glasses that have built-in eye tracking such as Vive Pro Eye [4] or AR such as Microsoft HoloLense 2 [5].

[3] https://docs.microsoft.com/en-us/workplace-analytics/myanalytics/use/dashboard-2
[4] https://www.vive.com/eu/product/vive-pro-eye/
[5] https://docs.microsoft.com/en-us/windows/mixed-reality/eye-tracking

8.3. Nascent Design Theory

To summarize the DSR project findings, I use the six core components of design theory that Gregor and Jones (2007) have introduced. Table 8.2, Table 8.3, Table 8.4 and Table 8.5 show the results of this DSR project in the form of nascent design theory.

The **first component** is the system's purpose and its scope. This component describes the goal of the system which is developed in this DSR project. The findings from this perspective are presented in Table 8.2. In this DSR project, I aimed to design and develop attentive information dashboards sensitive to the users' attention by tracking their eye movement data in real-time. The focus of developed attentive information dashboards is on increasing users' awareness about their previous visual behavior by providing individualized VAF. In this thesis, I focused on providing individualized VAF for two situations in which users have difficulty managing their limited attentional resources. First, I proposed supporting users during data exploration tasks on information dashboards (design cycle 2). In this case, an individualized VAF aims to increase users' self-awareness during data exploration and ultimately improve information processing performance. Second, supporting users in resuming an interrupted task (design cycle 3). In this case, I proposed gaze-based TRS as an individualized VAF when users return to their primary task after an interruption. I described the detailed motivation and goal of each DSR design cycle in Chapter 1, Section 1.1 and at the beginning of each design cycle.

The **second component** is justificatory knowledge. This component describes the theory that gives basis and explanation for the design. The summary of this component is presented in Table 8.2. For this DSR project, I used the knowledge described in attention, working memory, and Human Information Processing (HIP) theory. For attention, I used selective attention theories that focus on limitation of attention following Broadbent's filter theory (Broadbent, 1958), goal-directed attention that refers to the voluntary type of attention (Corbetta and Shulman, 2002), overt attention is considered as an extrinsic behavior such eye movements (Posner, 1980) and the eye-mind assumption that indicates where users are fixating is underlying their cognitive process such as allocating their attention (Just and Carpenter, 1980). For explaining different types of memories and their relationship, I focused on multi-model memory (Atkinson and Shiffrin, 1968). I also integrated the concept of working memory from Baddeley's model of working memory (Baddeley and Hitch, 1974) and the updated version of it (Baddeley, 2000). Moreover, I used the adapted version of HIP stages by Wickens et al. (2016) for explaining different stages of processing information on the dashboard and the role of attention and working memory on that. The foundations regarding these theories are discussed in Chapter 2, Section 2.2. Furthermore, for design cycle 3, I integrated the stages of interruption and resumption from (Trafton et al., 2003) to explain the users' attention shift procedure and the role of individualized VAF to support resuming interrupted tasks. The details are discussed in Section 7.5.1. Besides these theories, I leveraged prescriptive knowledge from existing studies in eye tracking, AUI, BI&A, and information dashboards explained in Section 2.3. Furthermore, I leveraged the identified studies in the conducted SLR study in Chapter 3 that focused on data exploration, and gaze-based TRS.

The **third component** describes the key constructs leveraged in this DSR project. Participants had the same task as data exploration in all four studies of the DSR project. Also, in all studies, the data exploration task had two phases: the first visit phase in which the participants started to explore the information dashboard and revisit phase in which participants had the chance to explore the same dashboard again after receiving VAF types. In addition to these two phases, in the Study V, the users had to conduct a secondary task in between these two phases as an interruption task. Table 8.3 shows a list of constructs for each DSR design cycle. As can be seen, in all design cycles, I used eye tracking data to analyze users' visual behavior from different perspectives. All studies involve the participants' performance in *"Attentional Resource Allocation"* in the revisit phase. With this construct, I examine the ability to ignore previously high-visited AOIs and to allocate attention to the previously low-visited AOIs. It was essential for tracking how the individualized VAF supported users in managing their limited attentional resources and compare it with the situation that users did not receive such support. Also, in all studies of the DSR project, except Study II, I measured the *"Attention Shift Rate"* to investigate the ability to select limited charts to process in the revisit phase rather than allocating attention to several AOIs. Besides, in studies II and IV, I measured user's *"Attentional Resource Management"* at the end of the task, explaining the participant's ability to allocate attention to all dedicated charts on the dashboard properly in a limited time. In studies II and IV, I also investigated the task resumption performance of the participant based on their eye movement data. For that, I measured the *"Resumption Success Rate"* construct that shows the percentage of users that could select the last AOI before interruption as the first AOI after the resumption. Furthermore, in Study V, I investigated the *"Resumption Lag"* construct as the time-period between finishing the secondary task and resuming the primary task. The usage of user's log data was only integrated with Study V to measure the *"Task Completion Time"* since the data exploration time was not fixed like in the other studies. I considered this construct as task performance for Study V. Besides that, I evaluated three designed highlighting methods as gaze-based TRS of Study V through survey questions. In this survey, I collected data for four constructs. First, *"Perceived Usefulness"* as the user's opinion about the usefulness level of each gaze-based TRS. Second, *"Perceived Ease of Use"* as the user's opinion about how easy it was to use each of the gaze-based TRS. Third, *"Self-awareness"* as the user's opinion about the influence of gaze-based TRS on self-awareness. Fourth, *"Behavioral Intention to Use"* as the user's opinion about the probability of using each gaze-based TRS in the future. The detail of how each of these constructs is measured for the conducted studies are discussed in each study separately.

The **fourth component** is capturing the principles of form and function. Table 8.4 shows a list of DPs derived by this DSR project for each design cycle. In design cycle 1, I conducted an exploratory study using eye tracking and reviewed existing literature to identify six MRs for designing attentive information dashboards. Second, I tested two general approaches for supporting attentional resource allocation by integrating the eye tracking technology in an eye tracking pilot study. One approach was the usage of eye movement data in real-time and the other one off-line usage of eye movement data from other users (e.g., experts) as VAF. Later, I derived two theoretically grounded DPs in design cycle 2 and three theoretically grounded DPs in design cycle 3 based on existing literature. First DP in both design cycles has a similar goal by enabling the information dashboard with tracking user's eye movement data in real-time. So, all in all, I presented four distinct DPs for designing attentive information dashboards that both support users in data exploration and resuming an interrupted task. Later I evaluated the effects of these DPs quantitatively in two separate large-scale eye tracking laboratory experiments as a suggested method to evaluate DSR projects (Pries-Heje et al., 2008; Venable et al., 2012). I explained the detailed description of DPs in design cycle 2 in Section 6.2 and design cycle 3 in Section 7.3.

The **fifth component** is focused on artifact mutability that discusses the changes of the artifact that is anticipated in theory. Table 8.5 shows a list of software artifacts designed and developed in this DSR project. In design cycle 1, I compared the effect of three VAF types with each other in an eye tracking pilot study. Two of them used off-line records of eye movement data, one with a proper example of attention allocation and the other one with an improper example of attention allocation from other users who did the same task. The third one shows the individualized VAF by tracking user's eye movement data in real-time and has the goal to increase user's self-awareness. Later in design cycle 2, I improved the design of individualized VAF and compared it with another software artifact that provides general feedback about attention in a text format in a large-scale eye tracking experiment. To design attentive information dashboards for the data exploration support with individualized VAF, I presented a system architecture with three subsystems. The details of this system architecture, the role of each subsystem, and the mapping to defined DPs are discussed in Section 6.3. Later in design cycle 3, I presented three software artifacts that use different highlighting methods (last point, heatmap, scanpath) as individualized VAF for resuming interrupted tasks, called gaze-based TRS. For designing individualized VAF as TRS, I presented a system architecture with four subsystems. The details of this system architecture, the role of each subsystem and the mapping to defined DPs are discussed in Section 7.4.

The **sixth component** describes the testable propositions. Study I was an exploratory study to investigate the role of limited attention and working memory on data exploration tasks. Study II was also an exploratory study to test the difference between two suggested solutions for VAF by integrating eye tracking technology (off-line and real-time use of eye movement data for VAF) in an eye tracking pilot study. Therefore, these two studies do not include any hypothesis to examine. Later in design cycle 2, I formulated three hypotheses for evaluating the effects of the DPs on information processing performance. The details of these hypotheses and the research model for this study are discussed in Section 6.4. The design cycle 3 was also an exploratory study to investigate the role of WMC on the effectiveness of different highlighting methods for gaze-based TRS. In this study, I evaluated the users' visual behavior from high and low WMC and summarized the findings. This study also does not include any hypothesis.

1	**Purpose and Scope**	• The aim is to develop attentive information dashboards with eye tracking technology to support users in processing information by managing limited attentional resources. Particularly, I focused on two scenarios that information dashboard users have difficulty to manage their limited attentional resources:
		  • Conducting data exploration tasks.
		  • Resume an interrupted data exploration task.
		
		• I proposed two theoretically grounded DPs for attentive information dashboards with individualized VAF that support data exploration, developed the software artifact and evaluated it in the lab experiment.
		
		• I proposed three theoretically grounded DPs for individualized VAF support task resumption, developed the artifact with three highlighting methods (heatmap, scanpath, latspoint) as gaze-based TRS and evaluated them in the lab experiment by including the role of WMC.

2	**Justificatory knowledge**	• Built on the attention-related theories as:
		  • **Attention as a limited resource:** Selective attention as Broadbent's Filter Model (Broadbent, 1958).
		  • **Voluntary attention allocation:** Goal-directed attention (Corbetta and Shulman, 2002).
		  • **Attention as extrinsic behavior (eye movement):** Overt attention (Posner, 1980).
		  • **Eye fixations as attention allocation:** Eye-mind assumption (Marcel A. Just and Carpenter, 1980).
		
		• Built on the memory-related theories as:
		  • **Different types of memory:** Multi-store model of memory (Atkinson-Shiffrin, 1968).
		  • **Working Memory:** Baddeley's model of working memory (Baddeley and Hitch, 1974), (Baddeley, 2000).
		
		• Leverage **HIP theory** to explain different steps of processing information adapting Wickens et al. (2015).
		
		• Leverage the **model of memory for goals** (Altmann & Trafton, 2002) and stages of interruption and resumption (Trafton et al. 2003) to explain the role of individualized VAF for task resumption support (Study V).
		
		• Leverage prescriptive knowledge from **existing studies** in the attentive UI and VAF discipline for data exploration and task resumption support.

Table 8.2.: Nascent design theory following Gregor and Jones (2007): purpose and justificatory knowledge.

3	**Constructs**	**Design Cycle 1**	• I considered three constructs in **Study II** using eye movement data: • **Attentional Resource Allocation:** User performance in allocating limited attention on previously high and low-attended AOIs and ignore previously high-attended AOIs. • **Attentional Resource Management:** The ability to distribute the attention properly among all stimulus on the screen. • **Resumption Success Rate:** The percentage of users in each group (low and high WMC) that could select the last AOI before interruption as the first AOI after the resumption. • I considered two constructs in **Study III** using eye movement data: • **Attentional Resource Allocation:** User performance in allocating limited attention to previously low-attended AOIs and ignoring previously high-attended AOIs in the revisit phase. • **Attention Shift Rate:** The centering of attention on limited set of AOIs on the dashboard.
		Design Cycle 2	• I considered three constructs in **Study IV** using eye movement data: • **Attentional Resource Allocation:** User performance in allocating limited attention on previously low-attended AOIs and ignore previously high-attended AOIs. • **Attention Shift Rate:** The centering of attention on limited set of AOIs on the dashboard. • **Attentional Resource Management:** The ability to distribute the attention properly among all AOIs on the dashboard.
		Design Cycle 3	• I considered four constructs in **Study V** for task resumption performance using eye movement data: • **Attentional Resource Allocation:** User performance in allocating limited attention on previously low-attended AOIs and ignore previously high-attended AOIs after each gaze-based TRS. • **Attention Shift Rate:** The centering of attention on limited set of AOIs before and after receiving each gaze-based TRS. • **Resumption Success Rate:** The percentage of users in each group (Gaze-based TRS) that could select the last AOI before interruption as the first AOI after the resumption. • **Resumption Lag:** The time-period between finishing the second task and resuming the primary task based on users' fixations. • I considered one task performance construct using interaction data: • **Task Completion Time:** How fast users could finish the data exploration task by checking their interaction data. • I considered four constructs for gaze-based TRS relevance using survey: • **Perceived Usefulness:** Users opinion about the usefulness level of the gaze-based TRS. • **Perceived Ease of Use:** How easy it was to use each of the highlighting methods as gaze-based TRS. • **Self-awareness:** Users' opinion about the influence of gaze-based TRS on self-awareness. • **Behavioral Intention to Use:** Users' opinion about the probability to use each gaze-based TRS in future.

Table 8.3.: Nascent design theory following Gregor and Jones (2007): constructs.

4	Principle of form and function	Design Cycle 1	• Based on the results from an eye tracking study for diagnostic purposes and existing literature, I derived meta-requirements for designing attentive information dashboard. • Later I tested two general approaches for providing VAF using eye movement data (real-time usage of eye movement vs. off-line records of eye movement).

		Design Cycle 2	• Based on existing literature, I derived two theoretically grounded design principles (DPs) for individualized VAF that support the data exploration task. Also, I evaluated the proposed design quantitatively in a laboratory experiment.
			
			    • **DP1:** Provide the information dashboard with the functionality to monitor the users' eye movement in real-time to analyze the users' attention, given that the user visually focuses the information dashboard.
			    • **DP2:** Provide the information dashboard with the functionality to display individualized VAF based on the monitoring of the users' eye movement to support users in improving information processing performance.
			
			• I suggested design features to support data exploration tasks on dashboards by providing dwell time on each chart as a time format.

		Design Cycle 3	• Based on existing literature, I derived three theoretically grounded design principles (DPs) for individualized VAF for supporting task resumption after an interruption. I also evaluated the proposed design and the role of WMC after a short-term interruption of a data exploration task, quantitatively in a laboratory experiment.
			
			    • **DP1 (similar to DP1 in Cycle 2):** Provide the information dashboard with the functionality to monitor the users' eye movement in real-time to analyze the users' attention, given that the user visually focuses the information dashboard.
			    • **DP2:** Provide the information dashboard with the ability to identify attention shifts to secondary task and resumption of primary task.
			    • **DP3:** Provide the information dashboard with gaze-based TRS in order to support users to resume their primary task.
			
			• I suggested design features to support task resumption after an interruption by providing three gaze-based highlighting methods (heatmap, scanpath, last point).

Table 8.4.: Nascent design theory following Gregor and Jones (2007): principle of form and function.

5	**Artifact mutability**	**Design Cycle 1**	• I discussed the mutability of information dashboards that provide VAF for data exploration, and the actual instantiation of the design in three software artifacts:
			  • **Artifact 1:** an information dashboard with individualized VAF.
			  • **Artifact 2:** an information dashboard with an example of **proper** attention allocation (off-line eye movement data).
			  • **Artifact 3**: an information dashboard with an example of **improper** attention allocation (off-line eye movement data).

		Design Cycle 2	• I discussed the mutability of information dashboards that provide VAF for data exploration, and the actual instantiation of the design in two software artifacts:
			  • **Artifact 1:** an information dashboard with **individualized VAF** (real-time eye movement data).
			  • **Artifact 2:** an information dashboard with **text-based explanations** about ARA challenges as general VAF.
			• I discuss the system architecture for attentive information dashboard that works with eye tracking technology and provide data exploration support.

		Design Cycle 3	• I discussed the mutability of the information dashboard that supports task resumption after an interruption, and the actual instantiation of the design in three software artifacts:
			  • **Artifact 1:** an information dashboard that provides **heatmap** highlighting method as gaze-based TRS.
			  • **Artifact 2:** an information dashboard that provides **scanpath** highlighting method as gaze-based TRS.
			  • **Artifact 3:** an information dashboard that provides **last point** highlighting methods as gaze-based TRS.
			• I discuss the system architecture for attentive information dashboard that works with eye tracking technology and provide gaze-based TRS.

6	**Testable propositions**	**Design Cycle 1**	• **Study I**: Explorative eye tracking study to investigate the role of limited attention and working memory while exploring information dashboards. • **Study II**: Explorative eye tracking study on the usage of off-line and real-time eye movement data as VAF.

		Design Cycle 2	• I formulated three hypotheses to test the effect of individualized VAF from three perspectives:
			  • **H1:** Providing individualized VAF results in better ARA performance in the revisit phase in comparison to providing generic VAF.
			  • **H2:** Providing individualized VAF results in lower ASR in the revisit phase in comparison to providing generic VAF.
			  • **H3:** Providing individualized VAF results in better ARM performance at the end of the task in comparison to providing generic VAF.

		Design Cycle 3	• Explorative eye tracking study on the role of WMC on the effectiveness of highlighting methods (heatmap, scanpath, last point) as gaze-based TRS.

Table 8.5.: Nascent design theory following Gregor and Jones (2007): artifact mutability and testable propositions.

8.4. DSR Knowledge Contribution

According to the DSR knowledge contribution framework by Gregor and Hevner (2013), this thesis and the conducted DSR project is an improvement since I successfully developed new solutions for existing problems. There are two major problems addressed in this DSR project. First, the difficulty of users in managing limited attentional resources while exploring information dashboards. Investigating existing research and the results from the exploratory study as Study II highlight this problem. Furthermore, the results from the SLR performed in Study I highlight that there is a lack of solutions for this problem by integrating real-time tracking of eye movement data. The IS researchers have called for the usage of eye trackers to design innovative systems (Davis et al., 2014; Dimoka et al., 2012; Riedl and Léger, 2016; vom Brocke et al., 2013), and enhance users' cognitive limitations. However, no study has examined using eye movement data for designing VAF for IS applications (Lux et al., 2018). Therefore, as a solution, in design cycle 2, I designed and developed an attentive information dashboard with eye tracking technology. In this solution, I used the users' eye movement data to design individualized VAF and increase users' awareness of their previous visual behavior. The results from a large-scale laboratory experiment show that this solution could enhance users' ability to manage their limited attentional resources while exploring information dashboards.

The second problem focuses on the frequent interruptions of task execution in workplaces (Czerwinski et al., 2004; Mark et al., 2008), and the difficulty of employees to resume an interrupted task (Hemp, 2009; Hodgetts et al., 2015; Mark et al., 2005). The result from the Study II highlights this problem for information dashboard users. Leveraging eye movement data to detect an interruption and provide TRS by highlighting previously attended areas proved to support users in task resumption (Göbel and Kiefer, 2019; Jo et al., 2015; Kern et al., 2010; Mariakakis et al., 2015). However, investigating the papers in the Study I shows that existing gaze-based TRS studies did not examine the interruption on information dashboards and data exploration tasks so far. Furthermore, existing studies have centered on the last point approach as highlighting method for gaze-based TRS, and the heatmap and scanpath were not investigated. Besides, none of the studies investigated the role of WMC on the effectiveness of gaze-based TRS. As a solution, I designed and developed an attentive information dashboard that supports task resumption after short-term IT-mediated interruption by providing gaze-based TRS (last point, heatmap, scanpath) as an individualized VAF. I investigated this solution in design cycle 3 and evaluated it in a large-scale laboratory experiment. The results show that the need for gaze-based TRS is different for users with high and low WMC. Notably, the heatmap highlighting method is supportive for low WMC users, while users with high WMC may not need gaze-based TRS for short-term IT-mediated interruptions.

Furthermore, this DSR project contributes to the field of IS research that focuses on integrating neurophysiological tools for IS application as NeuroIS (Dimoka et al., 2012). The IS researchers have emphasized the need for integration of DSR and NeuroIS field of designing innovative IS applications (Riedl and Léger, 2016; vom Brocke et al., 2013). Based on the list of possible contributions in the field of NeuroIS provided by Riedl and Léger

(2016), the designed attentive information dashboard related to the eighth contribution, using eye tracking as NeuroIS tool and delivering an IT artifact which tracks and adapts to the user's attentional state. Moreover, this DSR project contributes to the ninth contribution by providing individualized VAF as a live bio-feedback that assists users to control their limited attentional resources better.

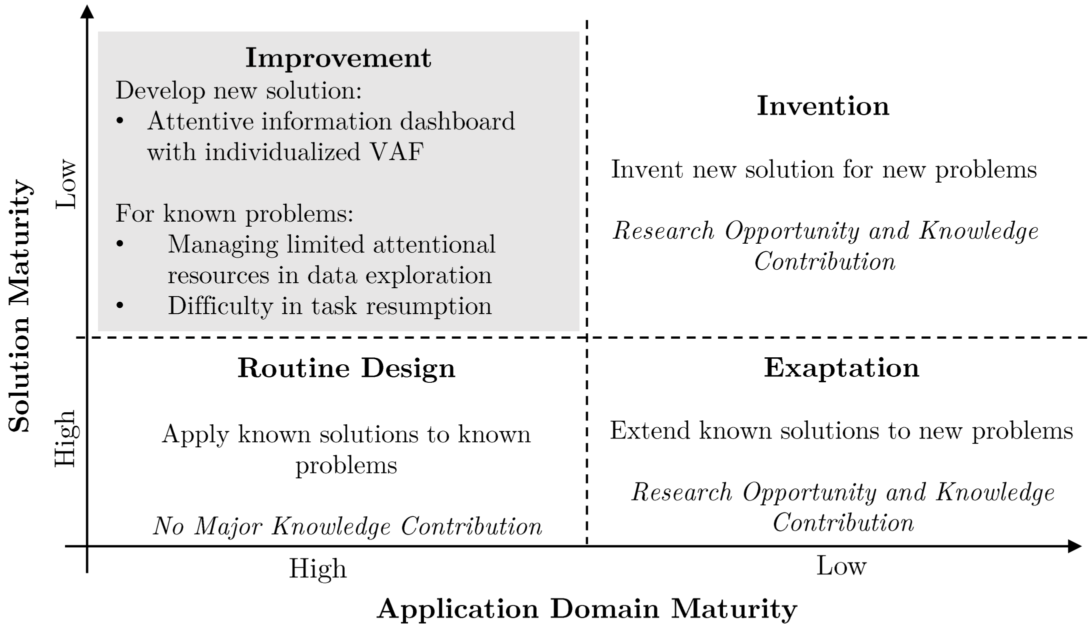


Figure 8.1.: DSR knowledge contribution based on Gregor and Hevner (2013).

8.5. Limitations and Future Research

All five studies in this thesis were conducted, emphasizing rigor, and relevance. However, some limitations need to be considered and addressed in future research. In the following, I first discuss limitations and future work for the SLR study conducted as Study I in this thesis. Later I investigate the limitations and possible future research for the DSR project, including the Studies II, III, IV, and V from different perspectives.

Study I

Due to the time limitation considered in selecting eye-based IIS papers for the SLR study, research studies before 2009 were not included in the review. As eye tracking studies have a longer history than that, there can be some promising studies that have not been considered in this SLR study. Therefore, I suggest investigating the history of eye-based IIS without any time limitation. In this study, I first provided a general conceptual framework and then analyzed the collected papers based on that. This framework was improved during the analysis phase and in iterative ways. Furthermore, I included opinions from knowledgeable researchers in conducting SLR studies and eye tracking. However, it might miss some aspects of designing eye-based IIS or detailed categories for each dimension (for example, reasoning dimension can include several subdimensions). As future work, there is a need to evaluate this framework in detail. Researchers can also develop a framework based on collected studies and compare it with the suggested one. Especially for some specific types of eye-based IIS, there may be more particular dimensions. Therefore, as future work, there is a possibility to focus on particular types of eye-based IIS (e.g., support collaboration, support interruption, summarization, etc.), provide a conceptual framework, and perform a SLR study for each perspective. As another limitation, the article collection and coding procedures were primarily done by only one researcher and might be biased. Therefore, no intercoder-reliability could be calculated, which can result in slightly different findings by other researchers. As future work, I suggest checking the intercoder-reliability by including more researchers in analyzing the papers. Furthermore, in this SLR study, I only focus on providing descriptive analysis about different dimensions of the eye-based IIS. Further studies can include relationship analysis between these dimensions by conducting a meta-analysis on collected data.

DSR Project

First, I presented the limitations and possible future works based on the apparatus used in this DSR project. The Tobii 4C eye tracker was the primary apparatus for all four studies (Studies II, III, IV and V) of the DSR project. I used this device for both design and evaluation purposes. Regarding the design purpose, this apparatus is known as a low-cost eye tracker and is mainly designed for eye-based interactive features. Also, the results from the Study I show that this apparatus is the most popular one for designing eye-based IIS. Such capability supports designing attentive information dashboards by tracking user's eye movement data in real-time and providing the individualized VAF that helps attention management. However, for the evaluation part, there are several devices in the market for evaluating user's visual behavior with higher accuracy than Tobii 4C eye tracker. By integrating devices with higher accuracy, there is a possibility of having access to high-resolution eye tracking data and promoting further aspects of user's visual behavior while working with individualized VAF. As an example, I needed to assign big AOIs while evaluating user's eye movement data. I considered each chart as an AOI and reported the analysis results based on that in all four studies. However, how the users allocated attention inside each chart with smaller AOIs can also include valuable information. Also, I did not use any eye movement analysis software to record and analysis eye movement data for the conducted studies. For Studies II and III, I used recorded dwell-time based on an integrated timer in the experimental software. For Study IV I used PyGaze (Dalmaijer et al., 2014) to extract fixation related values and for Study V, Tobii Pro SDK is used. All approaches represent the users' attention (Duchowski, 2017; Holmqvist et al., 2011) and the usage of techniques was stable within each study. In the future, to compare the users' visual behavior between studies, I suggest integrating one approach. Besides that, this device was limited to eye movement metrics and not accurate regarding pupil relevant data. By integrating an apparatus with higher accuracy, future research can extract pupil dilation to investigate user's cognitive load while using individualized VAF (Buettner et al., 2018; Fehrenbacher and Djamasbi, 2017; Perkhofer and Lehner, 2019). Also, using eye trackers for either designing or evaluation only includes recording overt attention. Duchowski (2017, p.13) has pointed out: *"... in all eye tracking work ... we* *assume that attention is linked to foveal gaze direction, but we acknowledge that it may not always be so".* To covert attention besides overt attention, future studies can use eye trackers beside biosignals like EEG (Léger et al., 2014) for evaluation purposes. Also, Roda and Thomas (2006) suggested to use eye trackers beside biosignals like heart rate, EEG, brain signals with fMRI, etc. for designing AUIs.

Second, I want to emphasize limitations and possible future works with regards to the information dashboard design. The information dashboards used in all four studies of the DSR project (Studies II, III, IV, and V) are not representing a real-world dashboard design. They all have the same design but with different content (check Appendices B, C, D, E). I selected this design for all studies to explore the users' goal-directed attention by controlling stimulus-driven attention. However, features to derive stimulus-driven attention (color, size, chart types, etc.) play an important role in the effectiveness of dashboards in real-world (Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). Besides the visual elements, I controlled for interactive features (e.g., filtering, zooming, etc.) in these dashboards as well, and all dashboards were static. Most dashboards in the market benefit from such features to support users in exploring information from different perspectives and affects its effectiveness (Pearson, 2013). For Study II, I decided to control these features since this is the fundamental study investigating the effects of limited attentional resources and WMC. However, these findings can be limited to the designed dashboard and difficult to generalize to all existing dashboards in the market. In future work, there is a need to investigate the role of the users' limited attention and WMC on the existing dashboard in the market. In studies III, IV and V, the same dashboard layout is used since I wanted to control the users' attention allocation in the revisit phase and identify the effects of VAF types. However, these effects can also be limited to this dashboard design, and there is a need to investigate such dashboard VAF types in with a real-world information dashboard.

Third, I want to mention some limitations with regards to the performed experiments:

- The participants in all four studies (Studies II, III, IV, V) of this DSR project are dominated by students. They were not daily users of information dashboards, which limit the generalizability of the results. Therefore, they have – similarly to novice users – little or no prior knowledge of the underlying experiment's process. Students can be considered an adequate and representative sample in the experimental setup (Burton-Jones and Meso, 2008). However, the users experience can play a role in managing limited attentional resources and their eye movements (Gegenfurtner et al., 2011). The users that already have experience with information dashboards may better allocate their attention to data exploration tasks. Therefore, the effectiveness of individualized VAF can be different for them. I suggest collecting eye movement data from users who already work with information dashboards and comparing the results as future work. Furthermore, long-term effects of attention management systems and their effects on human well-being are unknown (Anderson et al., 2018). Therefore, I suggest investigating the usage of attentive information dashboards and the suggested individual VAF types in long-term as field studies.

- The sample size of Studies II and III can be seen as a limitation in the case of a confirmatory study. Study I is considered an exploratory study to derive MRs for designing attentive information dashboards by exploring the users' visual behavior while working with dashboards. Study II is also considered as an eye tracking pilot study to compare using real-time or off-line records of eye movement data as VAF. Such studies with eye tracking focusing on problem identification require fewer participants than a study without eye tracking (Bojko, 2013, p. 163). Also, the review from Caine (2016) shows that the mean sample size for in-person studies using the eye tracking method is 21. Therefore, as all measures are derived from eye movement data in these two studies, I argue that the sample size in these two studies is synched with the first design cycle's purposes. However, as future work, there is an opportunity to conduct these studies with larger sample size for robust theorization and confirmatory studies.

- The results are limited to the data exploration task. In reality, the usage of an information dashboard is diverse, and users may use the information dashboards for visual search task besides data exploration. Furthermore, in the real-time BI&A systems, they may use it for monitoring or controlling (Lerch and Harter, 2001; Negash and Gray, 2008). Also the users may use information dashboards for planning to simulate various business scenarios (what if analysis) or in groups to ease the communications (Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012). As the future work for Study II, I suggest investigating the role of limited attention and WMC of information dashboard users for other tasks. Also, VAF types for Study III, IV, and V can be tested for other tasks beyond data explorations.

- In Studies II and III, all users received VAF, and it was created following an automatic invocation approach. This can limit the generalization of the results since users may need different invocation styles for such feedback. Gregor and Benbasat (1999) mentioned invocation styles as user-invoked, automatic, and intelligent. Further research should be done on different invocation styles for individualized VAF. Also, the time to provide VAF was fixed for all the participants, and they received it during the data exploration task. Based on Morana et al. (2017), there are three types of timing for providing such feedback, including concurrently, prospectively, and retrospectively. As future work, there is an opportunity to investigate the effectiveness of individualized VAF for data exploration in these different timings.

- I all studies, I measured the quality of information processing by considering the users' overall management of the attentional resources, rather than by the quality of their task performance. Previous studies have shown that the pattern of attention can explain the task performance (Bera et al., 2019). Engaging users to the information on dashboards may allow users to extract and remember more detail information (Healey and Enns, 2012). I suggest expanding the experimental setup with further constructs to investigate the influence of individualized VAF on users' performance.

- In Study V, the results are limited to the effects of three gaze-based TRS highlighting methods under consideration of different WMC as user characteristics, short-term external interruption. This limits the ability to generalize the findings for other types of tasks, interruptions, context, and user characteristics. Therefore, I suggest testing the provided highlighting methods in different situations as future work. As an example, there is a need to investigate how providing such gaze-based TRS supports users in long-term interruptions. Furthermore, I compared the effects of gaze-based TRS types on users with low and high WMC separately. As future work, it is possible to compare the impact of gaze-based TRS between two groups. Also, I divided the groups into high and low WMC following the previous categorization of these individual characteristics in IS research (Lerch and Harter, 2001). As future work, it is possible to consider the user's WMC values for the analysis rather than the categorization of the users.

- In Study II and V, the role of visuospatial WMC is investigated as individual characteristics and presented the results based on this individual difference. As future work, there is a possibility to investigate other cognitive abilities of the users such as encoding strategy, digit working memory span, personality, etc. while exploring information dashboards.

- All the studies are conducted in a controlled lab environment, limiting the generalizing of the results for real-world setup. Therefore, I suggest integrating the individualized VAF for data exploration and task resumption in a real-world information dashboard and test them in laboratory and field studies.

Fourth, the results from Studies III, IV, and V are limited to the VAF design. The design that uses for Study III and Study IV to support the data exploration task includes the gaze duration on each chart to remind users about their previous visual behavior. There is an opportunity to investigate different gaze visualizations (e.g., heatmap, scanpath, etc.) as another highlighting method for individualized VAF that supports data exploration. For instance, we suggested designing a dashboard called *"AttentionBoard"* and presented the initial steps of designing it by providing MRs and DPs (Langner et al., 2020). Based on that, an individualized VAF is in the form of dashboards and presents dynamic heatmap and scanpath to show previous attention allocation of the information dashboard users from different views. This type of individualized VAF can be useful for both data exploration and resuming interrupted tasks.

Fifth, this DSR project is limited to provide individualized VAF for data exploration and resuming interrupted tasks. However, there are several other situations in which users of information dashboards may need attention support features. For instance, in global organizations, many meetings take place virtually using collaboration technologies, and a major requirement for successful collaboration is allocating joint attention. A lack of joint attention leads to misunderstandings or inefficient virtual teamwork. Therefore, I suggest designing attentive information dashboards to support remote collaboration by sharing the user's gaze position to overcome the lack of joint attention. For that, Toreini et al.

(2018a) present a prototype and a pilot evaluation study to explore the effect of sharing gaze in a dyadic collaboration with an information dashboard. Also, findings from SLR study as Study I in this thesis shows different types of attention support features that can be used for information dashboard users.

Sixth, this DSR project is limited to integrate real-time eye movement data for information dashboard users. However, there is a possibility to design and test individualized VAF for other IS applications. For instance, Hummel et al. (2018) have suggested the usage of eye tracking technology to create attentive nudges with individualized VAF to support users not to miss information provided on nudges. Also, the example studies provided in the SLR study as the Study I in this thesis can be beneficial for existing IS applications.

Seventh, as the results from Study I show, an essential driver for adopting systems that integrate real-time eye movement data is the implementation of privacy features (Kunze et al., 2013; Steil et al., 2019). The developed attentive information dashboard and individualized VAF types in this study do not incorporate any mechanism for privacy aspects. As future work, there is a need to ensure that such systems respect the ethical and privacy aspects and considers the well-being of their users (Anderson et al., 2018).

9. Conclusion [1]

Human attention is known as a limited resource (Broadbent, 1958; Chun et al., 2011), and managing limited attentional resources is a challenge for users in the information-rich age (Gausby, 2015; Simon, 1971). However, having access to the enormous amount of data from various resources is beneficial for companies. With the use of big data technologies, companies collect and analyze data from various resources to assist users in making better decisions with BI&A systems (Chen et al., 2012). BI&A systems extract data from various resources, analyze it, derive insights, and present them to decision-makers in the form of information dashboards (Pauwels et al., 2009; Yigitbasioglu and Velcu, 2012) which are known as one of the most effective BI&A tools (Negash and Gray, 2008). The challenge for organizations is not to collect more information, but to use the information in an effective way (Lerch and Harter, 2001). Information dashboards come with strong potentials to support better decision making by providing information from different perspectives, but they challenge their users' limited attentional resources since they include a huge amount of information (Alberts, 2017; Dilla et al., 2010; Lurie and Mason, 2007; Yigitbasioglu and Velcu, 2012). Existing research on BI&A systems is focused on their business significance and widespread use and provide solutions regarding users' challenges in managing limited attentional resources is a research gap (Browne and Parsons, 2012; Chen and Lee, 2003; Davern et al., 2012; Niu et al., 2013). The main research question of this thesis was focused on, *"How to design attentive information dashboards for* BI&A systems that enhance users' ability to manage attentional resources?". In order to answer this research question, five break-down research questions were formulated and answered step-by-step in five studies. Besides, as users' eyes are known as a proper resource to track their attention, this thesis focused on designing attentive information dashboards by integrating eye tracking technology. Eye tracking technology has matured considerably in recent years, primarily because of the availability of cheaper, faster, more accurate, and easier to use eye trackers (Duchowski, 2017). Researchers have suggested to integrate eye trackers technology beyond evaluation purposes and use it for designing supportive features for BI&A systems (Silva et al., 2019). Also, the usage of this technology to design innovative IS applications is suggested by IS researchers (Davis et al., 2014; Dimoka et al., 2012; vom Brocke et al., 2013). Furthermore, HCI researchers have considered it as the primary technology for designing AUIs (Bulling, 2016; Majaranta and Bulling, 2014).

In the Study I, I conducted a SLR study on previous research focusing on eye-based interactive intelligent systems. As part of this study, a conceptual framework was developed, state-of-the-art and future research directions were identified. Building on these results and following DSR methodology, three design cycles for designing attentive information dashboards were performed. The first design cycle includes two studies: Study II investigated attention problems of information dashboard users under consideration of their individual

[1] This Chapter is based on the following studies which are published or in work: Toreini and Morana (2017), Toreini et al. (2018c), Toreini et al. (2018b), Toreini and Langner (2019), Toreini et al. (2020b), Toreini et al. (2020c), Toreini and Maedche (2020), Toreini et al. (2020a)

WMC. The results showed that users with high and low WMC have different difficulties in managing their attentional resources. Study III evaluated different potential solutions for supporting data exploration tasks using eye movement data. These solutions were named VAF types that aimed to increase users' awareness about their ARA performance and let them improve it. The results showed that providing individualized VAF integrating real-time eye movement data supports users in managing their attentional resources better than general VAF with integrated off-line recordings of eye movement data. In the second design cycle, I designed and evaluated an attentive information dashboard for the data exploration task. In Study IV, theoretically grounded DPs were articulated, instantiated as a software artifact, and evaluated in a large-scale laboratory experiment. The results from analyzing the users' eye movement data reveals that the suggested DPs have a positive effect on users' ability to manage limited attentional resources during data exploration tasks. In the third design cycle, I investigated attentive information dashboards to support resuming interrupted tasks. Study V instantiated three software artifacts using different gaze-based highlighting methods (last point, heatmap, scanpath) and evaluated them in a large-scale laboratory experiment by considering short-term IT-mediated interruptions and the role WMC. The results demonstrate the need for personalization of such support under consideration of users' WMC.

According to the DSR knowledge contribution framework by Gregor and Hevner (2013), this thesis and the conducted DSR project is an improvement since it successfully developed new solutions (attentive information dashboards) to existing problems (managing limited attentional resources). Furthermore, this thesis contributes to the intersection of IS and HCI fields by providing prescriptive knowledge in the form of nascent design theory for designing attentive information dashboards. This knowledge can support both researchers and practitioners. The proposed attentive information dashboards are the first BI&A systems presented in the IS field that use real-time eye movement data for designing advanced built-in attention support functions. Practitioners can leverage the findings from this thesis for integrating attention support functionality into existing BI&A platforms or designing further attentive IS applications that support users in managing limited attentional resources. I believe the findings of this thesis will serve as a reference for researchers and practitioners that focus on enhancing users' attention management capability by designing innovative IS applications with eye tracking technology.

Appendix

A. Study I

A.1. List of Papers for Literature Review

1. Fujii and Rekimoto (2019)
2. Kütt et al. (2019)
3. Bozkir et al. (2019)
4. Akkil et al. (2018)
5. Zhang et al. (2017)
6. D'Angelo and Begel (2017)
7. Newn et al. (2017)
8. Akkil and Isokoski (2016)
9. Kajan et al. (2016)
10. Toyama et al. (2015)
11. Wetzel et al. (2014)
12. Booth et al. (2013)
13. Dostal et al. (2013)
14. Ishii et al. (2013)
15. Pomarjanschi et al. (2012)
16. Buscher et al. (2012)
17. Alt et al. (2012)
18. Xu et al. (2008a)
19. Cheng et al. (2010)
20. Vrochidis et al. (2011)
21. D'Mello et al. (2012)
22. Cai and Lin (2012)
23. Kern et al. (2010)
24. Cheng et al. (2018)
25. Nguyen and Liu (2016)
26. Tremblay et al. (2018)
27. D'Mello et al. (2017)
28. Deza et al. (2017)
29. Mariakakis et al. (2015)
30. Hutt et al. (2019)
31. Taylor et al. (2015)
32. Jo et al. (2015)
33. Xu et al. (2008b)
34. D'Angelo and Gergle (2016)
35. Rozado et al. (2015)
36. Garrido et al. (2014)
37. Giannopoulos et al. (2012)
38. Umemoto et al. (2012)
39. Trösterer et al. (2015)
40. Siirtola et al. (2019)
41. Mills et al. (2019)
42. D'Angelo and Gergle (2018)
43. Qvarfordt et al. (2010)
44. Neider et al. (2010)
45. Higuch et al. (2016)
46. Schneider and Pea (2013)
47. Brennan et al. (2008)

A.2. Coding Tables for Literature Review

	User Context							Physical Context												Task								
	Social			User Profile				Type		Digital Applications										Type								
Authors	Individual Level	User Agent	Team Level	Age	Gender	Experience Level	Vision Status	Digital Env.	Real-World Env.	Driving Simulator	Websites	Exploration Tool	Multi-Display Software	AR/VR Application	Collaboration Tool	Gaming Software	Cellphone App	Training Platforms	Reading Tool	Gaming	Reading	Writing	Browsing / Search	Monitoring	Driving	Remote Physical Task	Learning	Programming
(Fujii and Rekimoto, 2019)	X				X			X										X									X	
(Kütt et al., 2019)			X	X	X	X		X							X							X						
(Bozkir et al., 2019)	X			X	X	X		X		X								X							X			
(Akkil et al., 2018)			X	X	X	X			X						X											X		
(Zhang et al., 2017)			X	X	X			X				X			X								X					
(D'Angelo and Begel, 2017)			X					X							X													X
(Newn et al., 2017)			X	X	X	X		X								X				X								
(Akkil and Isokoski, 2016)			X	X	X			X		X															X			
(Kajan et al., 2016)	X			X	X	X		X			X												X					
(Toyama et al., 2015)	X							X						X									X					
(Wetzel et al., 2014)	X			X		X		X								X				X								
(Booth et al., 2013)	X			X	X	X			X														X					
(Dostal et al., 2013)	X				X			X					X										X					
(Ishii et al., 2013)		X						X							X								X					
(Pomarjanschi et al., 2012)	X			X	X	X		X		X															X			
(Buscher et al., 2012)	X			X	X	X		X			X								X		X							
(Alt et al., 2012)	X			X				x			X												X					
(Xu et al., 2009)	X							X											X		X							
(Cheng et al., 2010)	X			X	X	X		x			X												X					
(Vrochidis et al., 2011)	X							x			X												X					
(D'Mello et al., 2012)	X			X	x			X										X									X	
(Cai and Lin, 2012)	X			X	X	X		X		X															X			
(Kern et al., 2010)	X			X	X			X		X													X					
(Cheng et al., 2018)	X			X			X	X											X		X							
(Nguyen and Liu, 2016)	X			X		X		X										X									X	
(Tremblay et al., 2018)	X						X	X					X											X				
(D'Mello et al., 2017)	X							X											X		X							
(Deza et al., 2017)	X							X										X					X					
(Mariakakis et al., 2015)	X			X	X	X	X	X									X				X							
(Hutt et al., 2019)	X			X	X			X										X									X	
(Taylor, 2015)	X						X	X								X								X				
(Jo et al., 2015)	X			X	X		X	X											X		X							
(Xu et al., 2008)	X							X			X												X					
(D'Angelo and Gergle, 2016)			X	X	X	X	X	X								X							X					
(Rozado et al., 2015)	X			X				X			X												X					
(Garrido et al., 2014)	X			x	X	X		X					X											X				
(Giannopoulos et al., 2012)	X			X	X	X		X				X											X					
(Umemoto et al., 2012)	X				X	X		X			X												X					
(Trösterer et al., 2015)			X	X	X	X		X		X					X										X			
(Siirtola et al., 2019)			X	X	X		X	X							X								X					
(Mills et al., 2019)	X			X	X	X		X											X		X							
(D'Angelo and Gergle, 2018)			X	X	X	X		X				X			X								X					
(Qvarfordt et al., 2010)	X			X	X		X	X				X											X					
(Neider et al., 2010)			X				X	X				X			X								X					
(Higuch et al., 2016)			X	X				X							X											X		
(Schneider and Pea, 2013)			X	X	X	X		X				X			X			X									X	
(Brennan et al., 2008)			X					X				X			X								X					

Table A.1.: Coding table of eye-based IIS literature review: context and task.

	Eye Tracking Technology										Experimental Setup							
	Apparatus Type					Hardware Provider			Price		Method		Study Design					Size
Authors	Desktop-Mounted	Head-Mounted	Webcam	Virtual Reality	Smartphone Cam.	Tobii	Others	Name	High-Cost	Low-Cost	Laboratory	Field	Between-Subject	Mixed Factorial	Within-Subject	Single User/Group	Case Study	No. of Users
(Fujii and Rekimoto, 2019)	X					X		Tobii 4C		X	X		X					6
(Kütt et al., 2019)	X					X		Tobii 4C		X	X		X					40
(Bozkir et al., 2019)				X			X	HTC-Vive with Pupil-Labs	X		X		X					16
(Akkil et al., 2018)	X					X		Tobii T60	X		X				X			24
(Zhang et al., 2017)	X					X		Tobii EyeX		X	X				X			16
(D'Angelo and Begel, 2017)	X					X		Tobii TX300 / Tobii EyeX	X	X	X				X			24
(Newn et al., 2017)	X					X		Tobii EyeX		X	X				X			27
(Akkil and Isokoski, 2016)	X					X		Tobii T60	X		X				X			12
(Kajan et al., 2016)	X					X		Tobii TX300	X		X				X			15
(Toyama et al., 2015)		X					X	SMI Glasses/Brother AirScouter	X		X					X		12
(Wetzel et al., 2014)		X					X	EyeLink II	X		X				X			31
(Booth et al., 2013)		X					X	SMI Glasses	X		X		X					20
(Dostal et al., 2013)			X				X	Webcam (self gaze detector)		X		X					X	1
(Ishii et al., 2013)	X					X		Tobii X120	X		X					X		10
(Pomarjanschi et al., 2012)	X						X	SMI RED250	X		X		X					30
(Buscher et al., 2012)	X					X		Tobii 1750	X		X		X					32
(Alt et al., 2012)	X					X		Tobii X120	X		X				X			12
(Xu et al., 2009)			X				X	Webcam (Opengazer)		X	X					X		12
(Cheng et al., 2010)	X	X					X	ASL 6000 / ASL RS H6	X		X				X			9
(Vrochidis et al., 2011)	X						X	faceLAB 5		X	X					X		8
(D'Mello et al., 2012)	X					X		Tobii T60	X		X				X			48
(Cai and Lin, 2012)	X					X		Tobii X50	X		X				X			20
(Kern et al., 2010)	X					X		Tobii X120	X		X				X			16
(Cheng et al., 2018)		X					X	MultiGaze (self dev. device)		X	X					X		11
(Nguyen and Liu, 2016)	X					X		Tobii EyeX		X	X		X					16
(Tremblay et al., 2018)	X						X	SmartEye Pro	X		X		X					99
(D'Mello et al., 2017)	X					X		Tobii TX300	X		X		X					104
(Deza et al., 2017)	X						X	EyeLink 1000	X		X				X			18
(Mariakakis et al., 2015)					X		X	Phone Cam. (self gaze detector)		X	X				X			17
(Hutt et al., 2019)	X						X	EyeTribe		X		X				X	X	135
(Taylor, 2015)	X						X	GazePoint GP3		X	X		X					44
(Jo et al., 2015)	X					X		Tobii X60	X		X				X			13
(Xu et al., 2008)			X				X	Webcam (Opengazer)		X	X					X		5
(D'Angelo and Gergle, 2016)	X						X	Eyetribe		X	X				X			36
(Rozado et al., 2015)	X					X		Tobii X1		X	X		X					20
(Garrido et al., 2014)			X				X	Webcam (self gaze detector)		X	X				X			12
(Giannopoulos et al., 2012)		X					X	Ergoneers Dikablis	X		X				X			40
(Umemoto et al., 2012)	X					X		Tobii T60	X		X					X		8
(Trösterer et al., 2015)	X						X	SmartEye Pro	X		X				X			20
(Siirtola et al., 2019)	X					X	X	Tobii T60 / myGaze	X	X	X			X				24
(Mills et al., 2019)	X					X		Tobii TX300	X		X			X				69
(D'Angelo and Gergle, 2018)	X					X		Tobii 4C		X	X			X				96
(Qvarfordt et al., 2010)	X					X		Tobii X120	X		X				X			8
(Neider et al., 2010)		X					X	EyeLink II	X		X		X					32
(Higuch et al., 2016)	X					X		Tobii EyeX		X	X		X					8
(Schneider and Pea, 2013)	X					X		Tobii X1		X	X		X					42
(Brennan et al., 2008)		X					X	EyeLink II	X		X		X					40

Table A.2.: Coding table of eye-based IIS literature review: eye tracking technology and experimental setup.

	Sense																			Reasoning							Focus	
	Gaze-based							Fixation-based					Saccade			Pupil		Others		Type							Type	
Authors	Gaze Position	Gaze Duration	Gaze Transition	Mutual Gaze	Visit Counts	Gaze Depth	Gaze Presence	Fixation Position	Fixation Duration	Number of Fixation	First Fixated	Last Fixated	Number of Saccades	Saccade Direction	Saccade Length	Pupil Dilation	Dilation Speed	Scanpath	Global Eye Feature	Engagement	Relevance/Interesting	Attention Switching	Uncertainty	Confidence	Mind Wandering	Intention	User Adaptation	System Adaptation
(Fujii and Rekimoto, 2019)										X			X								X							X
(Kütt et al., 2019)				X																	X						X	
(Bozkir et al., 2019)	X															X					X							X
(Akkil et al., 2018)	X																				X						X	
(Zhang et al., 2017)				X						X											X						X	
(D'Angelo and Begel, 2017)	X																				X						X	
(Newn et al., 2017)								X		X								X			X						X	
(Akkil and Isokoski, 2016)	X																				X						X	
(Kajan et al., 2016)		X			X					X		X									X							X
(Toyama et al., 2015)						X														X								X
(Wetzel et al., 2014)			X						X	X			X					X			X		X	X				X
(Booth et al., 2013)										X											X							X
(Dostal et al., 2013)	X															X					X	X					X	
(Ishii et al., 2013)		X	X	X											X	X				X								X
(Pomarjanschi et al., 2012)	X																				X							X
(Buscher et al., 2012)									X					X	X						X							X
(Alt et al., 2012)		X							X	X										X	X							X
(Xu et al., 2009)										X											X							X
(Cheng et al., 2010)									X	X	X					X					X							X
(Vrochidis et al., 2011)									X	X						X	X				X							X
(D'Mello et al., 2012)	X																			X	X							X
(Cai and Lin, 2012)								X												X	X							X
(Kern et al., 2010)												X									X	X					X	
(Cheng et al., 2018)												X									X	X					X	
(Nguyen and Liu, 2016)		X					X	X													X	X					X	X
(Tremblay et al., 2018)								X	X												X	X						X
(D'Mello et al., 2017)																			X						X			X
(Deza et al., 2017)								X		X			X								X							X
(Mariakakis et al., 2015)							X					X		X							X	X				X	X	
(Hutt et al., 2019)																			X						X			X
(Taylor, 2015)																X					X	X					X	
(Jo et al., 2015)								X				X									X						X	
(Xu et al., 2008)								X													X							X
(D'Angelo and Gergle, 2016)	X																				X						X	
(Rozado et al., 2015)								X													X							X
(Garrido et al., 2014)	X																					X						X
(Giannopoulos et al., 2012)								X	X												X						X	
(Umemoto et al., 2012)	X																				X					X		X
(Trösterer et al., 2015)	X																				X						X	
(Siirtola et al., 2019)	X																				X						X	
(Mills et al., 2019)																			X						X			X
(D'Angelo and Gergle, 2018)				X				X	X	X								X			X						X	
(Qvarfordt et al., 2010)		X						X	X												X						X	
(Neider et al., 2010)								X													X						X	
(Higuch et al., 2016)								X													X						X	
(Schneider and Pea, 2013)	X																				X						X	

Table A.3.: Coding table of eye-based IIS literature review: sense-reasoning and focus.

	Perception Outcome														Behavior Outcome												
	Status		Measures												Status		Measures										
Authors	Yes	No	Distraction	Frustration	Challenge	Fun	Nervousness	Ease of Use	Satisfaction	Correctness	Usefulness	Mental Workload	Confidence	Collab. Quality	Yes	No	Engagement	Attention Allocation	Search Strategy	Change in Attitude	Reading Speed	Attention Shift	Gaze Overlap	Objective Workload	User's Interactions	Conversation Analysis	Global Bias
(Fujii and Rekimoto, 2019)	X										X					X											
(Kütt et al., 2019)	X										X			X		X											
(Bozkir et al., 2019)		X													X									X			
(Akkil et al., 2018)	X													X	X											X	
(Zhang et al., 2017)	X		X					X			X	X				X											
(D'Angelo and Begel, 2017)	X										X				X		X						X				
(Newn et al., 2017)	X							X			X					X											
(Akkil and Isokoski, 2016)	X										X		X			X											
(Kajan et al., 2016)	X															X											
(Toyama et al., 2015)	X										X					X											
(Wetzel et al., 2014)	X			X	X	X	X								X			X									
(Booth et al., 2013)		X													X			X									
(Dostal et al., 2013)	X										X				X							X			X		
(Ishii et al., 2013)	X													X	X		X										
(Pomarjanschi et al., 2012)		X													X							X			X		
(Buscher et al., 2012)		X														X											
(Alt et al., 2012)		X													X		X	X		X							
(Xu et al., 2009)		X														X											
(Cheng et al., 2010)	X							X	X						X									X			
(Vrochidis et al., 2011)		X														X											
(D'Mello et al., 2012)	X								X						X		X					X					
(Cai and Lin, 2012)	X		X						X	X	X					X											
(Kern et al., 2010)	X								X		X					X											
(Cheng et al., 2018)	X								X		X				X							X					
(Nguyen and Liu, 2016)		X													X										X		
(Tremblay et al., 2018)	X											X			X			X									
(D'Mello et al., 2017)	X															X											
(Deza et al., 2017)		X													X			X									
(Mariakakis et al., 2015)	X											X			X						X	X					
(Hutt et al., 2019)		X														X											
(Taylor, 2015)		X													X			X						X			X
(Jo et al., 2015)	X										X				X			X									
(Xu et al., 2008)		X														X											
(D'Angelo and Gergle, 2016)		X													X											X	
(Rozado et al., 2015)		X														X											
(Garrido et al., 2014)		X														X											
(Giannopoulos et al., 2012)	X								X		X				X										X		
(Umemoto et al., 2012)		X														X											
(Trösterer et al., 2015)	X		X							X	X	X			X			X									
(Siirtola et al., 2019)	X										X					X											
(Mills et al., 2019)		X														X											
(D'Angelo and Gergle, 2018)	X								X						X				X							X	
(Qvarfordt et al., 2010)	X								X			X			X			X	X								
(Neider et al., 2010)		X													X			X					X				
(Higuch et al., 2016)	X										X			X	X			X									
(Schneider and Pea, 2013)	X		X											X	X			X					X	X			X
(Brennan et al., 2008)		X													X			X	X							X	

Table A.4.: Coding table of eye-based IIS literature review: perception and behavior.

	User Performance									System Performance				
	Status		Measures							Status		Measures		
Authors	Yes	No	Reaction Time	Completion Time	Driving	Self Report	Comprehension	Effectiveness	Accuracy	Yes	No	Accuracy	Running Time	Network Traffic
(Fujii and Rekimoto, 2019)	X								X		X			
(Kütt et al., 2019)	X			X					X		X			
(Bozkir et al., 2019)	X				X						X			
(Akkil et al., 2018)	X			X							X			
(Zhang et al., 2017)	X			X					X		X			
(D'Angelo and Begel, 2017)	X			X		X			X	X			X	
(Newn et al., 2017)	X								X		X			
(Akkil and Isokoski, 2016)	X				X					X		X		
(Kajan et al., 2016)	X			X						X		X		
(Toyama et al., 2015)		X								x		X		
(Wetzel et al., 2014)		X									X			
(Booth et al., 2013)	X			X					X		X			
(Dostal et al., 2013)		X									X			
(Ishii et al., 2013)	X								X	X		X		
(Pomarjanschi et al., 2012)	X		X						X		X			
(Buscher et al., 2012)		X								X		X		
(Alt et al., 2012)		X									X			
(Xu et al., 2009)		X								X		X		
(Cheng et al., 2010)	X			X						X		X		
(Vrochidis et al., 2011)		X								X		X		
(D'Mello et al., 2012)	X					X			X		X			
(Cai and Lin, 2012)	X								X		X			
(Kern et al., 2010)	X			X							X			
(Cheng et al., 2018)	X								X		X			
(Nguyen and Liu, 2016)	X			X					X		X			
(Tremblay et al., 2018)		X									X			
(D'Mello et al., 2017)	X						X			X		X		
(Deza et al., 2017)	X						X		X		X			
(Mariakakis et al., 2015)	X						X			X		X		
(Hutt et al., 2019)		X								X		X		
(Taylor, 2015)	X		X						X		X			
(Jo et al., 2015)	X								X		X			
(Xu et al., 2008)		X								X		X		
(D'Angelo and Gergle, 2016)	X			X					X		X			
(Rozado et al., 2015)		X								X			X	X
(Garrido et al., 2014)	X								X		X			
(Giannopoulos et al., 2012)	X			X				X			X			
(Umemoto et al., 2012)		X								X		X		
(Trösterer et al., 2015)	X				X						X			
(Siirtola et al., 2019)	X		X						X		X			
(Mills et al., 2019)	X			X		X	X				X			
(D'Angelo and Gergle, 2018)	X		X	X							X			
(Qvarfordt et al., 2010)	X								X		X			
(Neider et al., 2010)	X		X						X		X			
(Higuch et al., 2016)	X			X					X		X			
(Schneider and Pea, 2013)	X						X				X			
(Brennan et al., 2008)	X		X								X			

Table A.5.: Coding table of eye-based IIS literature review: performance.

B. Study II

B.1. Experimental Software

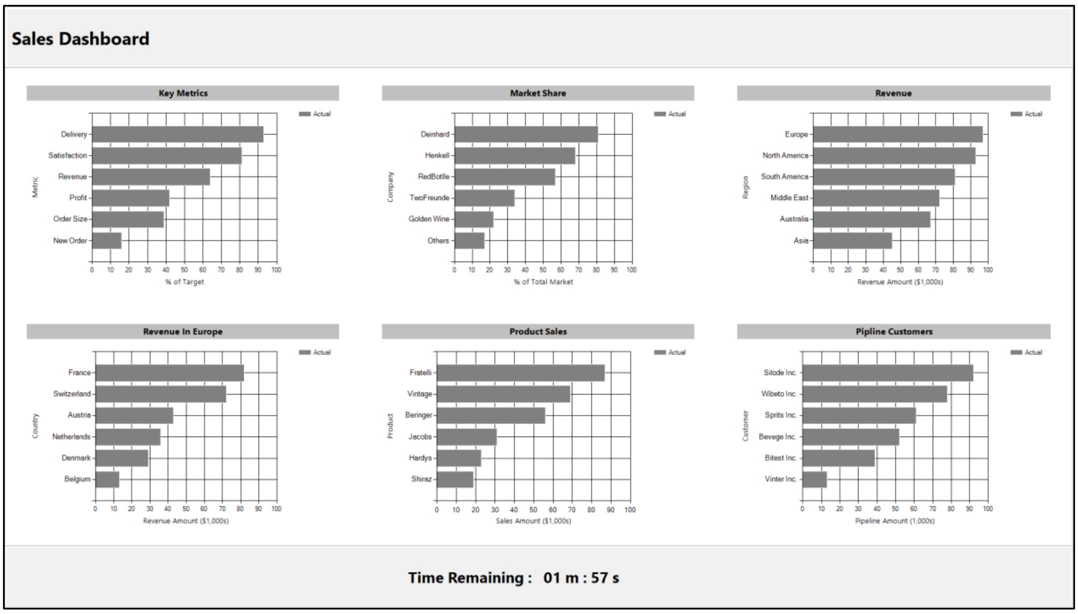


Figure B.1.: The information dashboard layout used in Study II.

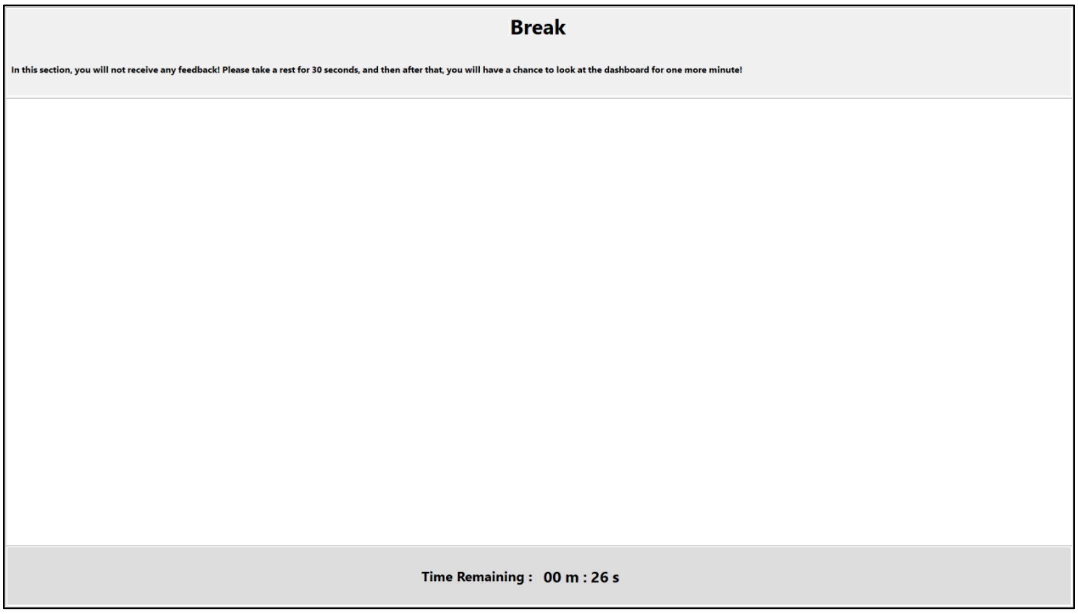


Figure B.2.: The break page as an interruption used in Study II.

B.2. Further Analysis

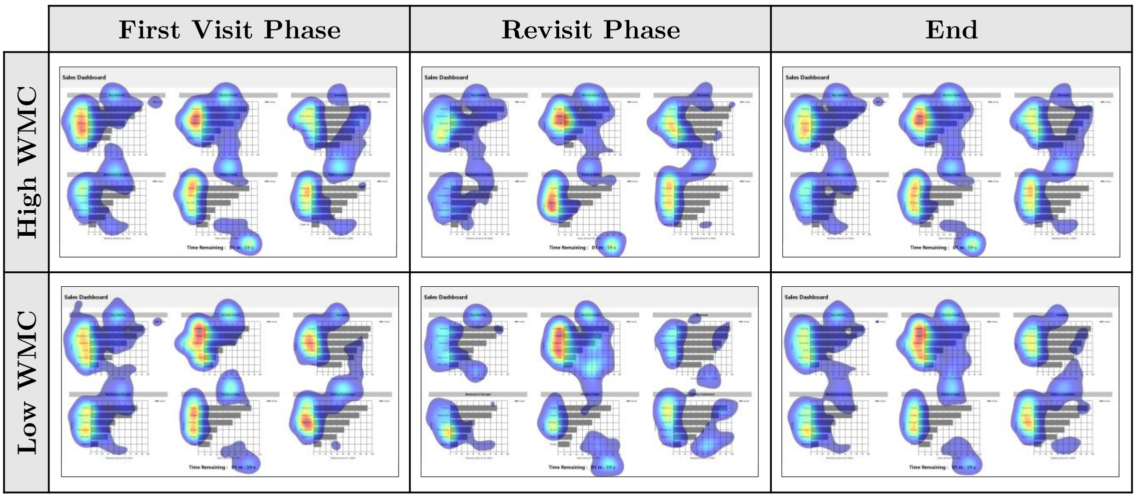


Figure B.3.: The heatmaps of users with high and low WMC in three phases of the experiment in Study II.

C. Study III

C.1. Experimental Software

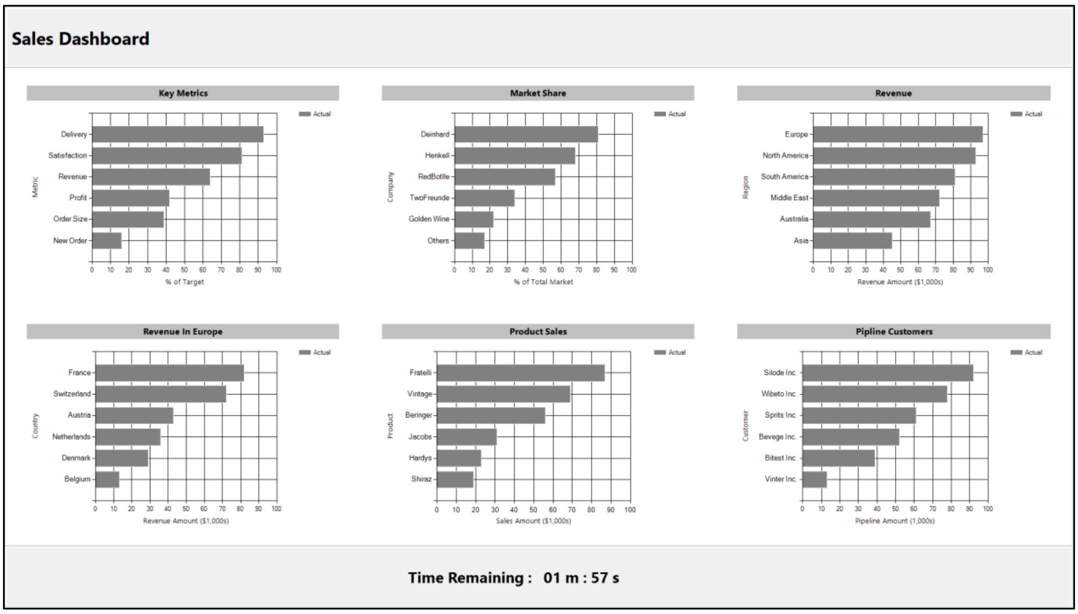


Figure C.1.: The information dashboard layout used in the first round of Study III.

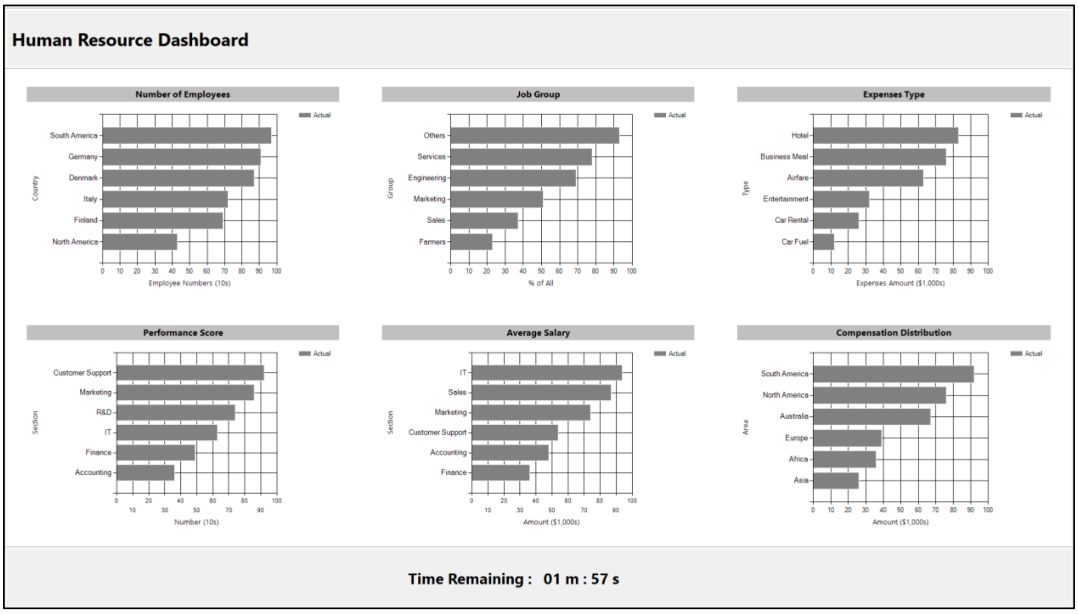


Figure C.2.: The information dashboard layout used in the second round in Study III.

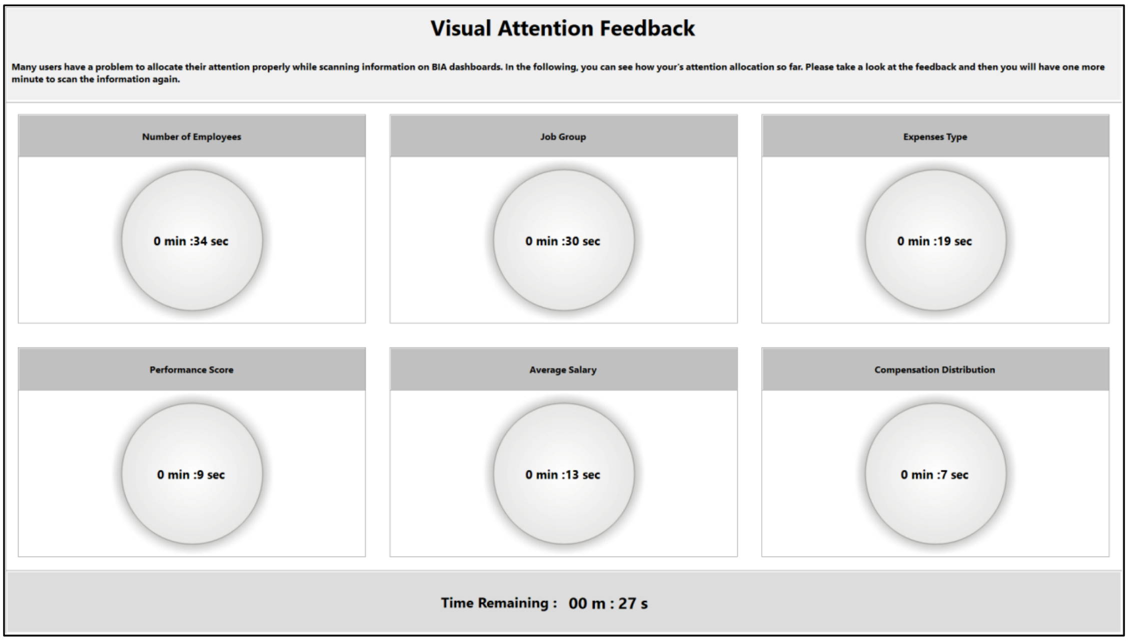


Figure C.3.: Example of VAF design used in the second round in Study III.

C.2. Further Analysis

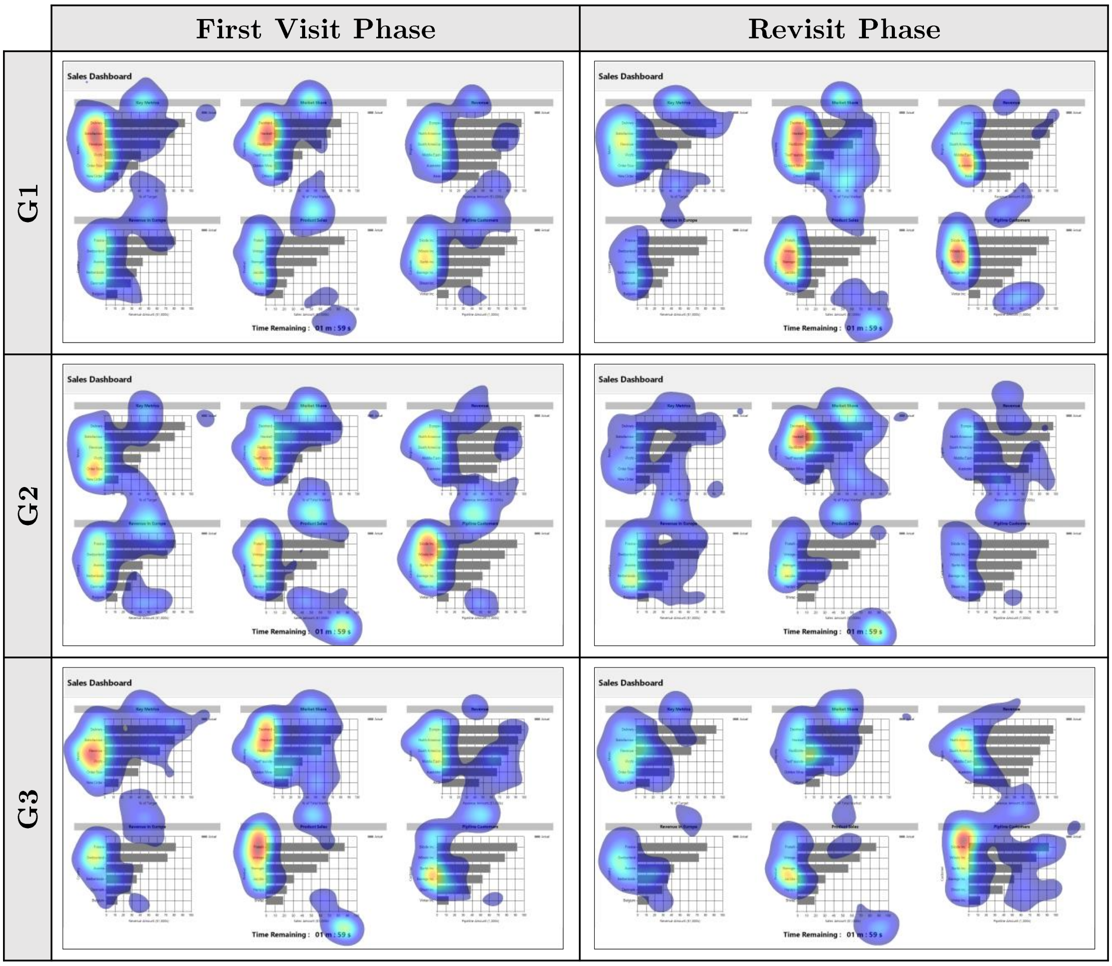


Figure C.4.: The heatmaps of users in first round of the experiment in Study III.

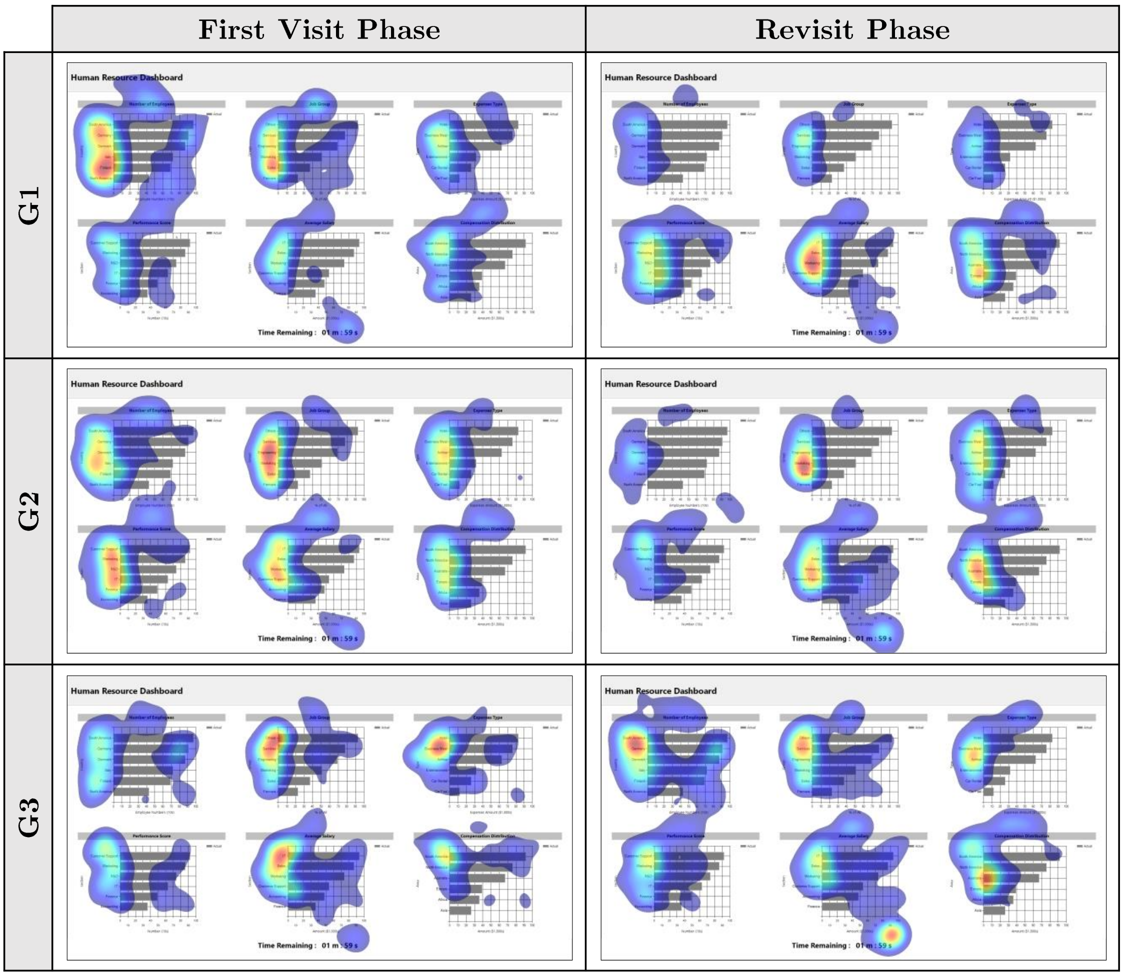


Figure C.5.: The heatmaps of users in second round of experiment in Study III.

D. Study IV

D.1. Experimental Software

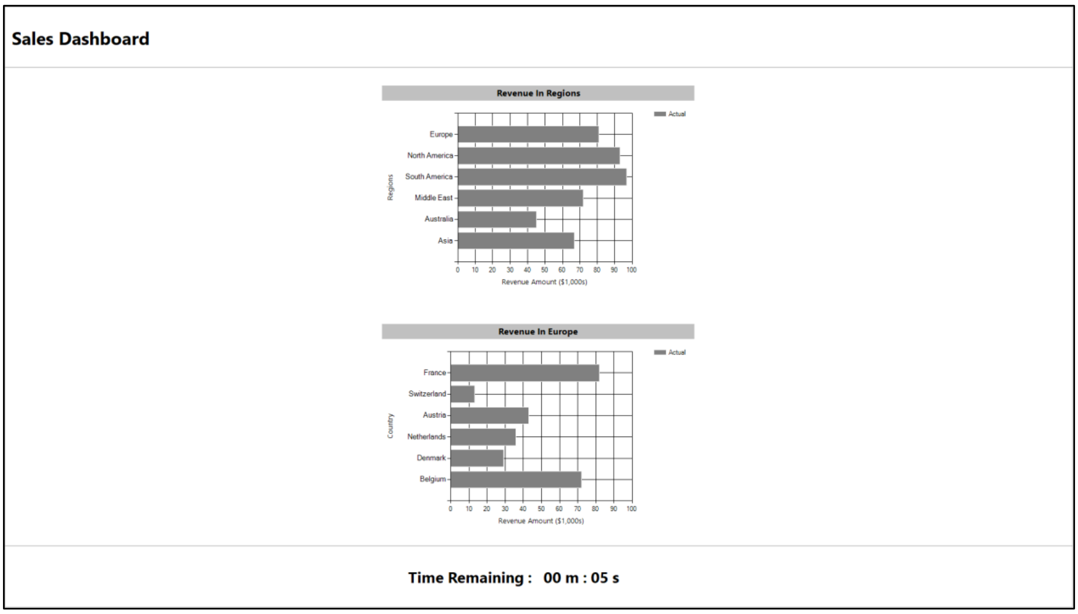


Figure D.1.: Simplified information dashboard used as the learning phase in Study IV.

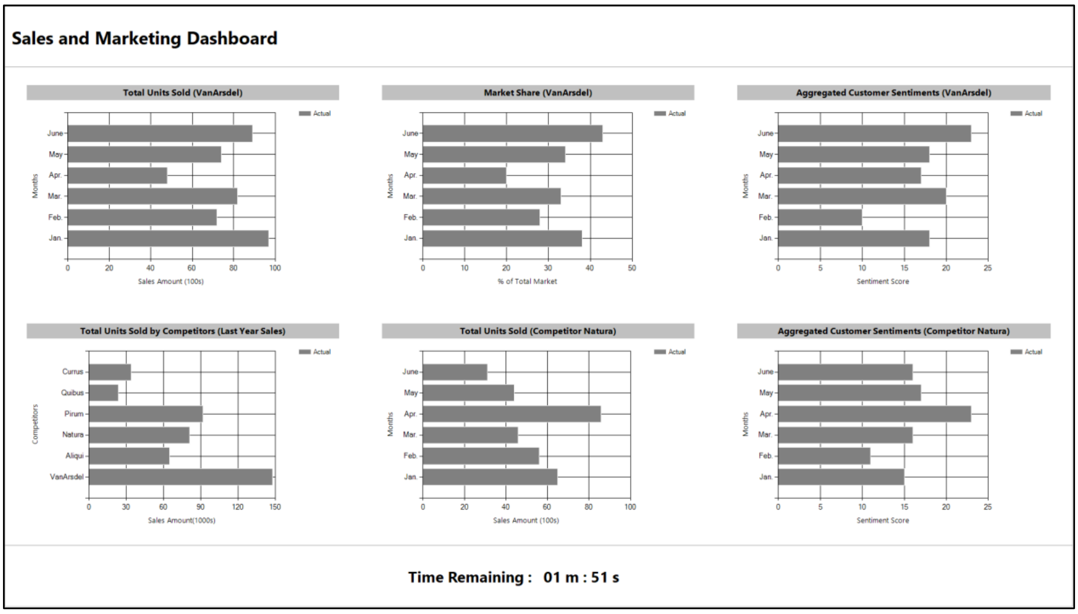


Figure D.2.: The information dashboard layout used in Study IV.

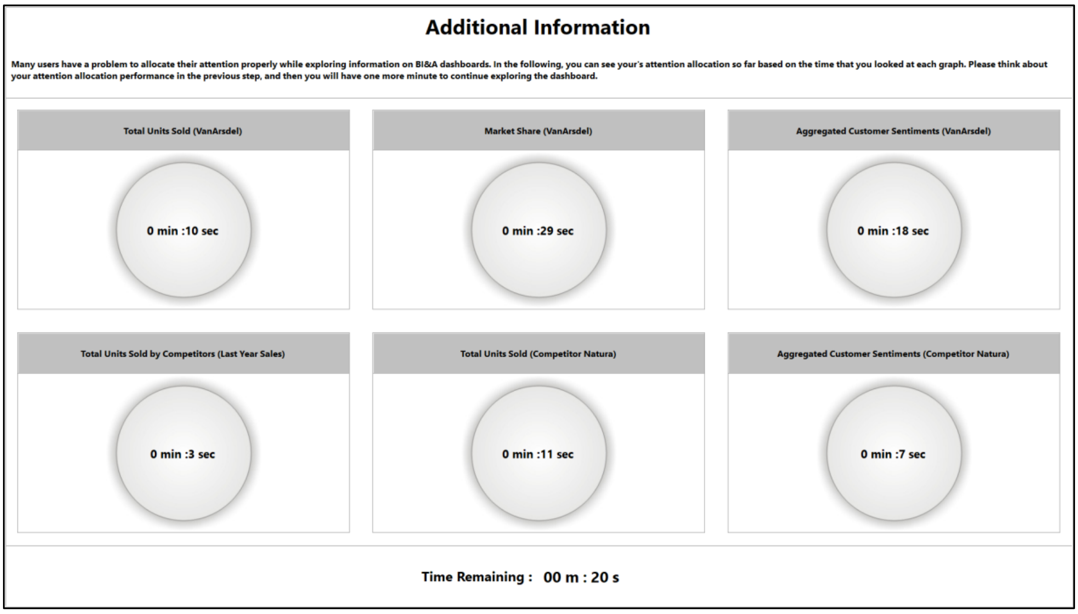


Figure D.3.: An example of individualized VAF used in Study IV.

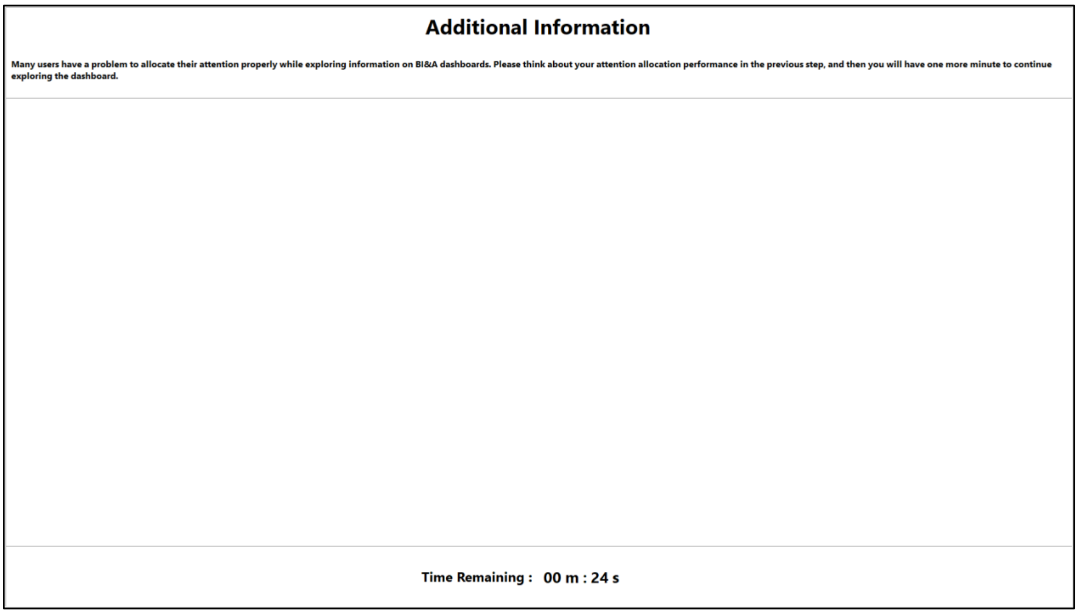


Figure D.4.: The general VAF as a text-based explanation used in Study IV.

D.2. Survey Items

Controls	Items	Measure
Age	• Please specify your age	-
Gender	• Please specify your gender	-
Experience Level	• Using the BI&A dashboard is a new experience for me. • Using the BI&A dashboard is not similar to anything that I've done before. • Using the BI&A dashboard is different from other experiences I have had.	Moore, G.C. (1989) Likert Scale 1 to 7

Table D.1.: Control variables and items used for Study IV.

D.3. Further Analysis

Control Variable	Conditions	Mdn	Mean	SD	W	P	R
Age	Individualized VAF	22.5	22.77	2.75	851.5	0.10	-0.167
	General VAF	24	24.06	3.8			
Experience Level	Individualized VAF	5	5	1.38	856.5	0.11	-0.163
	General VAF	5.67	5.42	1.43			
WMC – Corsi Span	Individualized VAF	6	6.01	0.84	1139.5	0.50	-0.068
	General VAF	5.5	5.94	1.09			
WMC – Digit span	Individualized VAF	7	7.32	1.27	1074.5	0.88	-0.015
	General VAF	7	7.25	1.33			
Note: * p<0.05, **p<0.01							

Table D.2.: Comparing the control variables – wilcoxon signed-rank test.

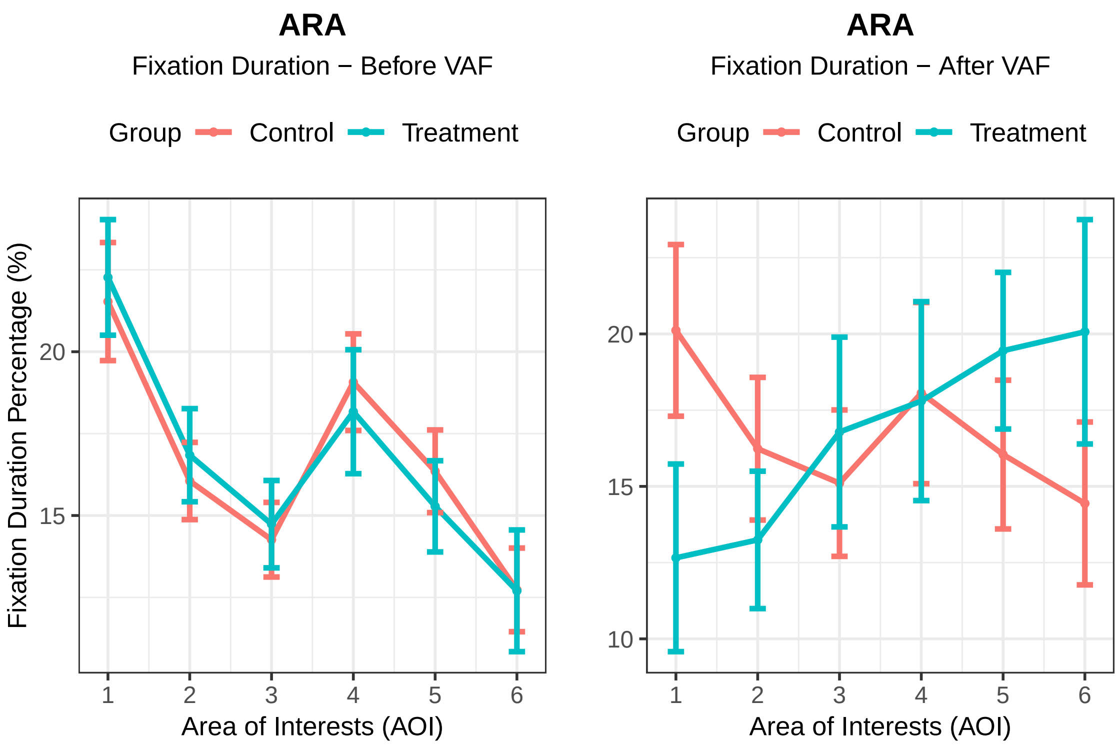


Figure D.5.: Distribution of fixation duration values before and after VAF types.

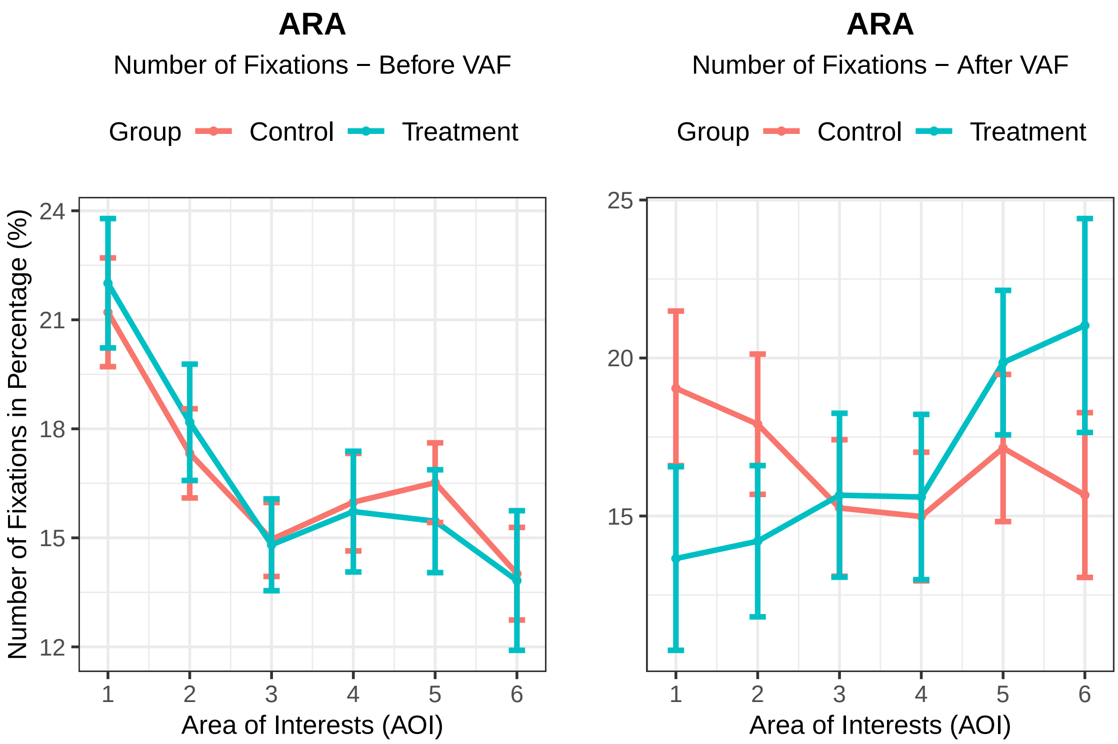


Figure D.6.: Distribution of number of fixations before and after VAF types.

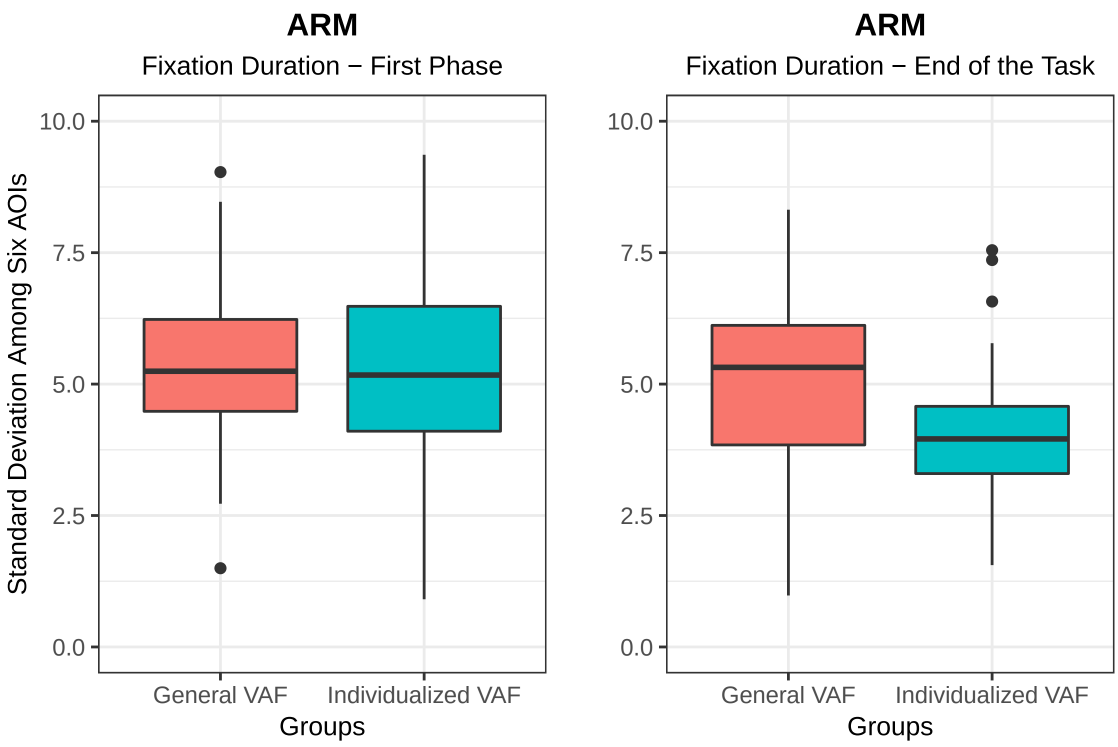


Figure D.7.: ARM of the users in the first and end of the data exploration tasks based on fixation duration values.

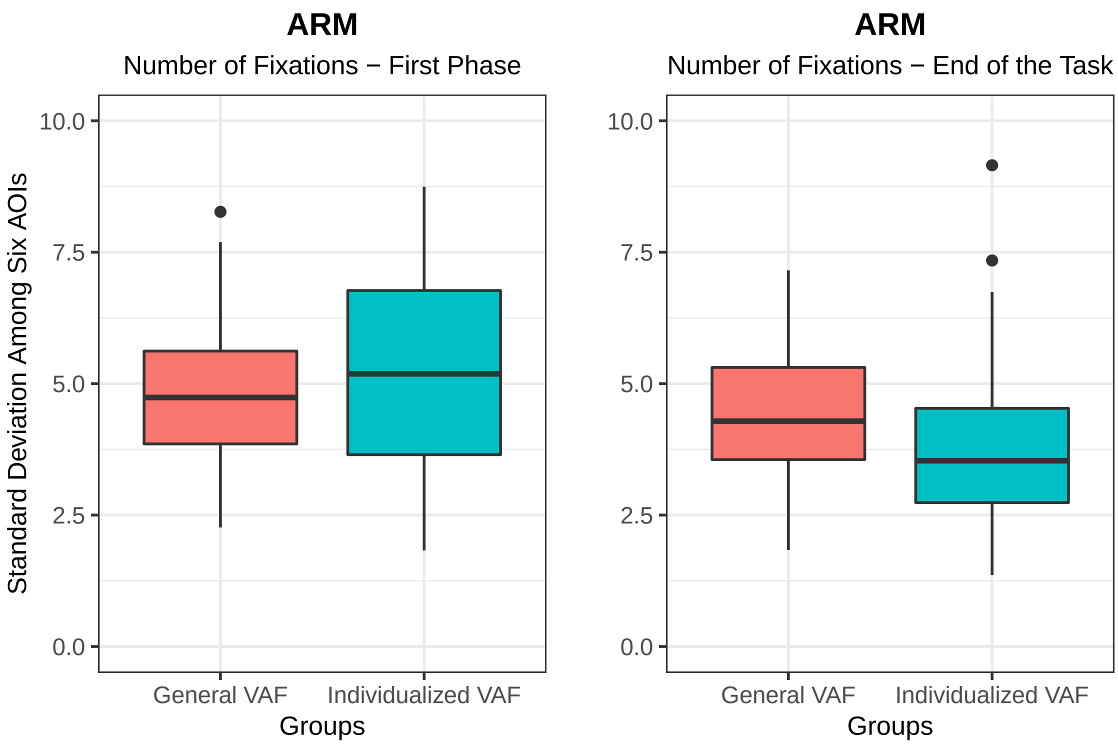


Figure D.8.: ARM of the users in the first and end of the data exploration tasks based on number of fixation values.

E. Study V

E.1. Experimental Software

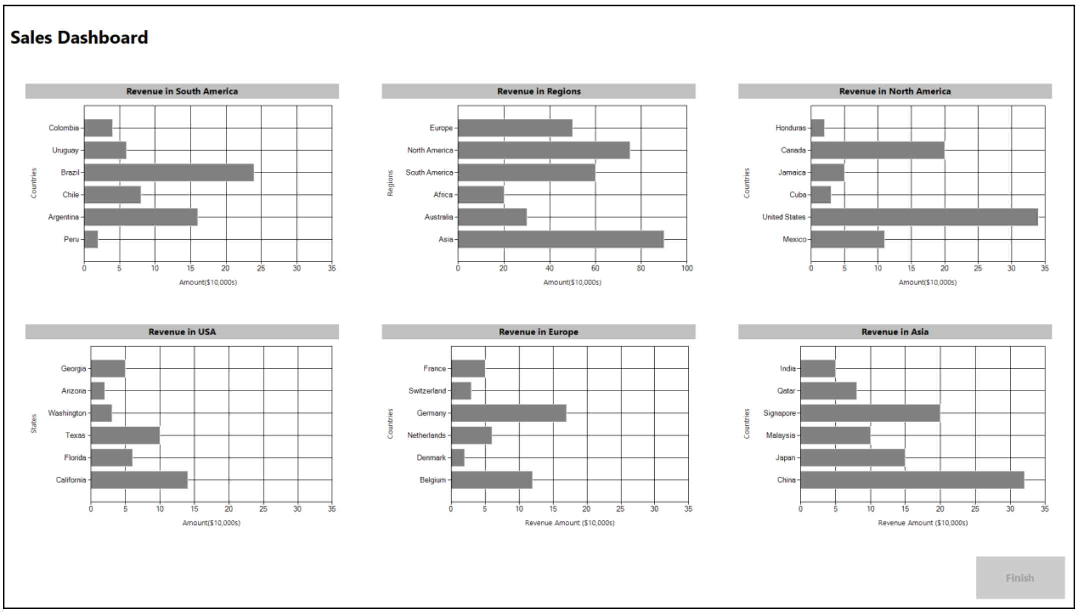


Figure E.1.: First information dashboard used in Study V.

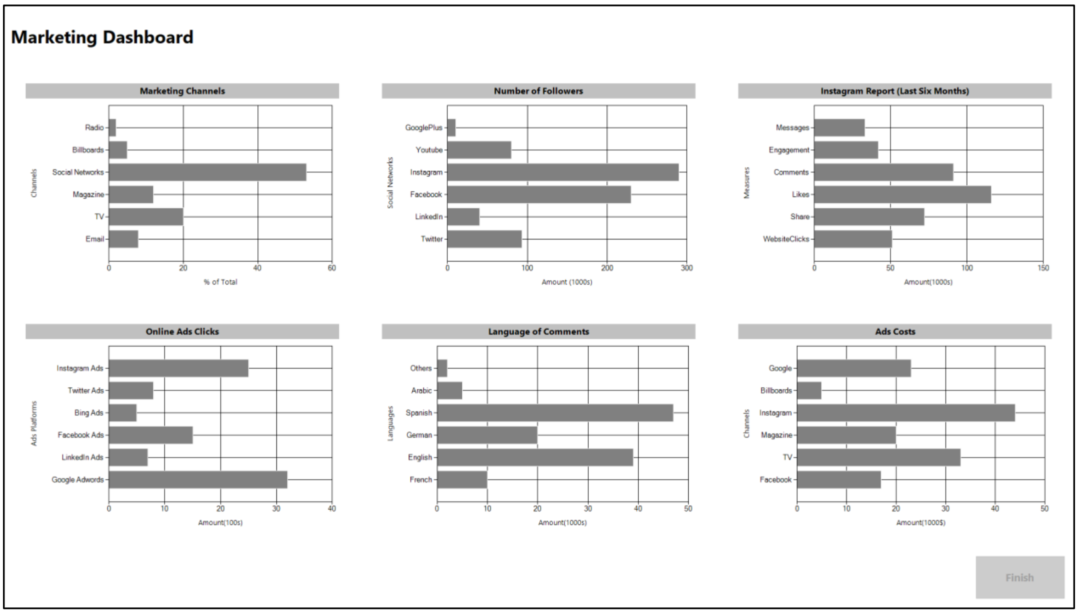


Figure E.2.: Second information dashboard used in Study V.

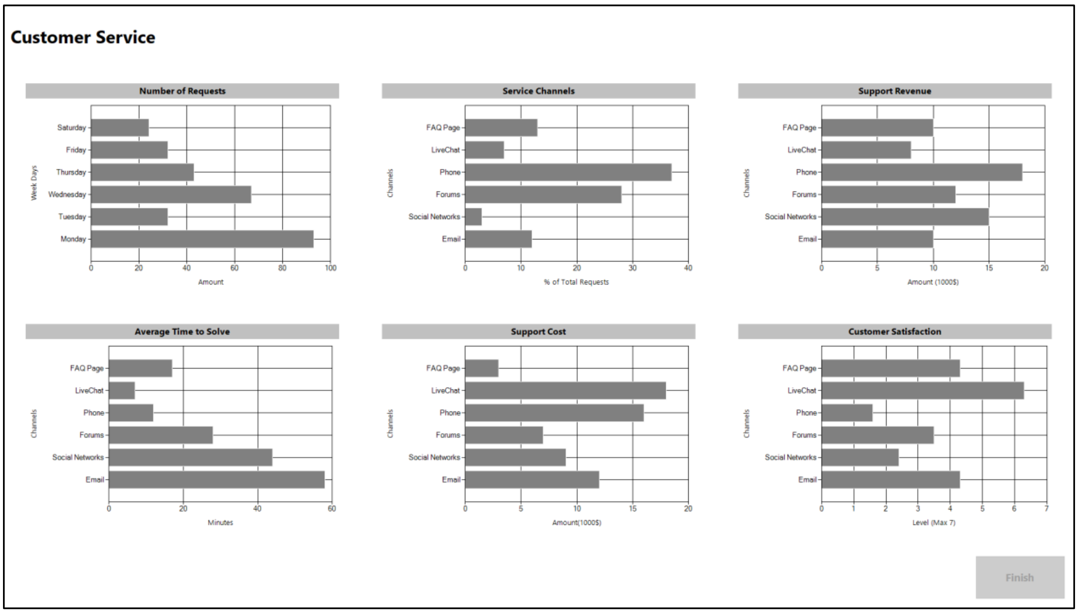


Figure E.3.: Third information dashboard used in Study V.

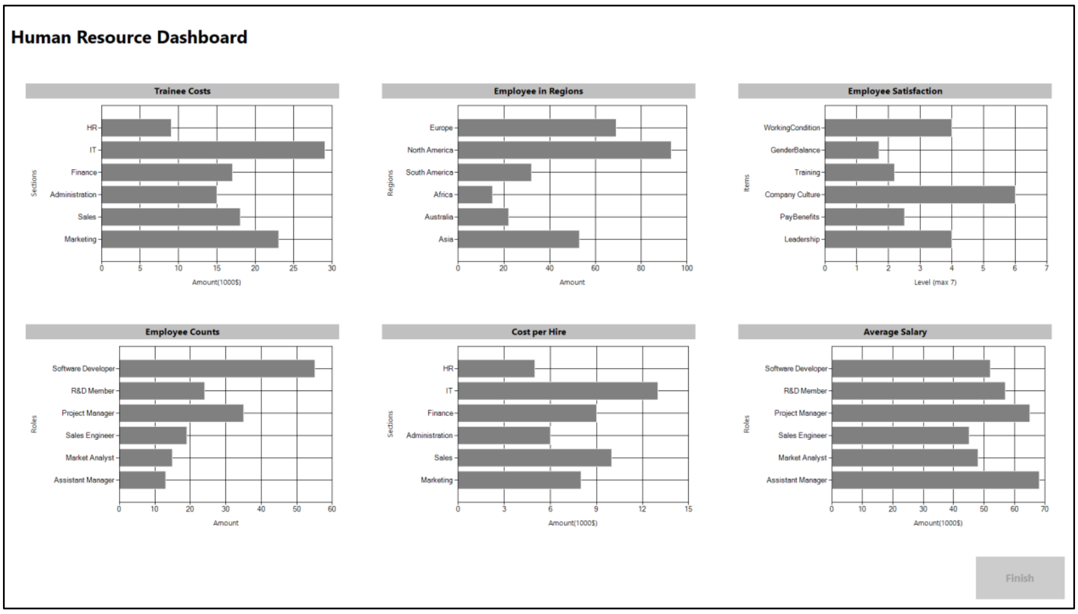


Figure E.4.: Fourth information dashboard used in Study V.

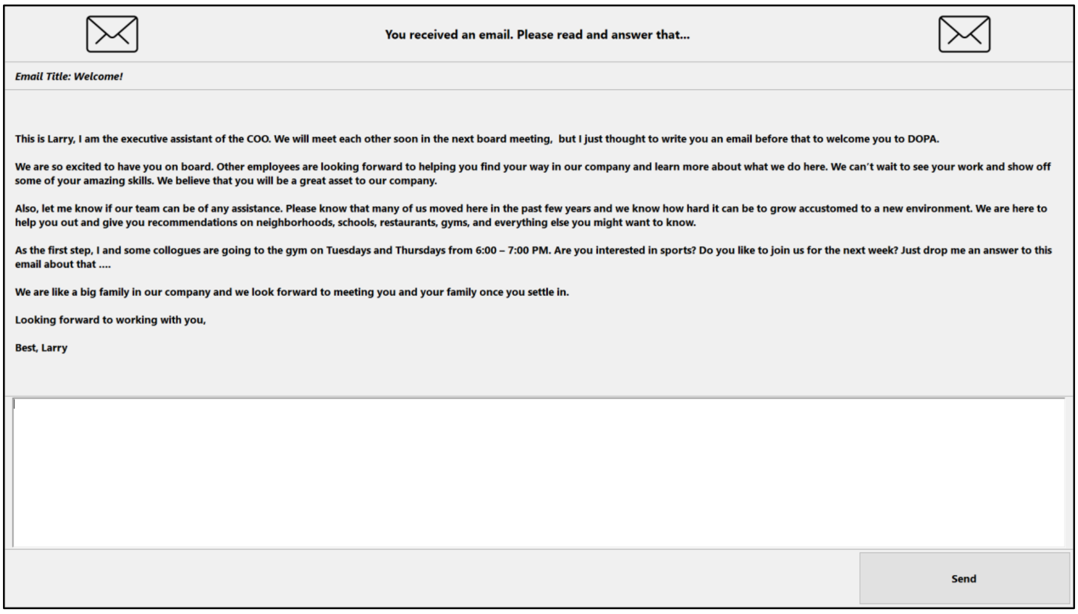


Figure E.5.: First e-mail used as an IT-mediated Interruption in Study V.

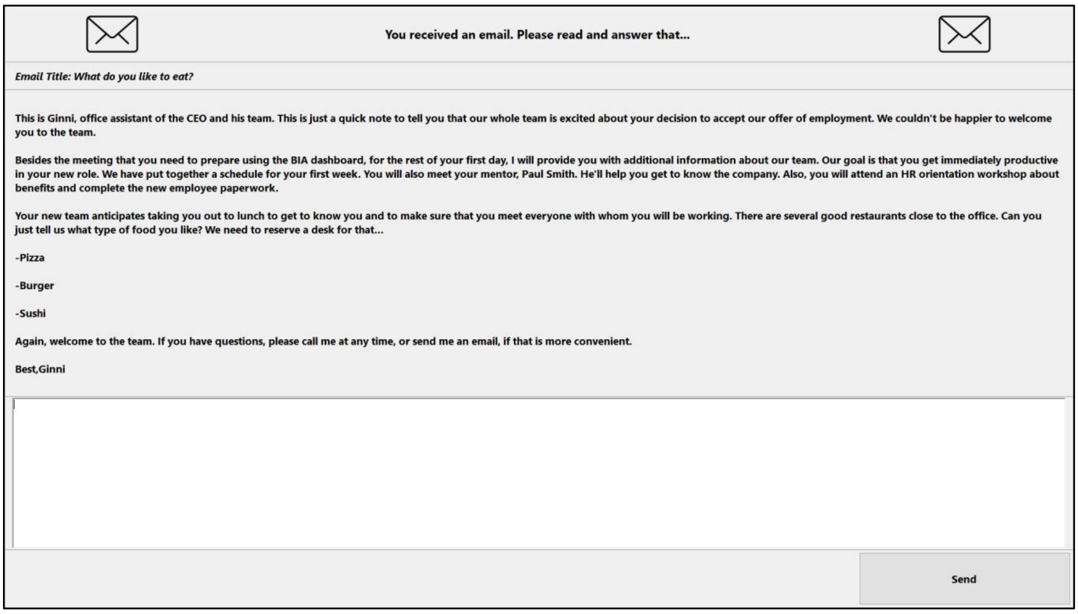


Figure E.6.: Second e-mail used as an IT-mediated Interruption in Study V.

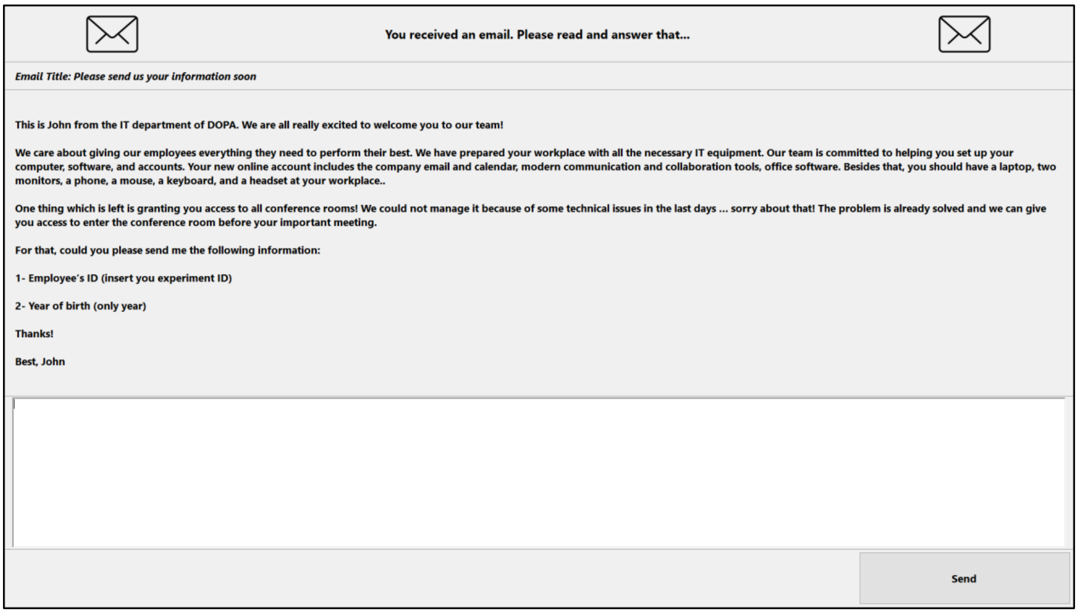


Figure E.7.: Third e-mail used as an IT-mediated Interruption in Study V.

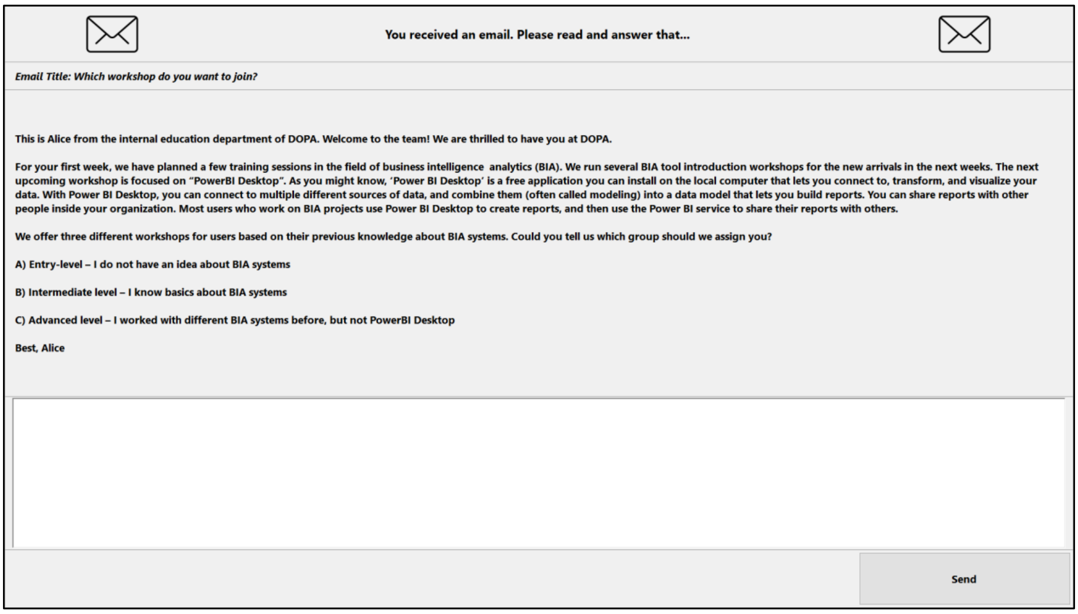


Figure E.8.: Fourth e-mail used as an IT-mediated Interruption in Study V.

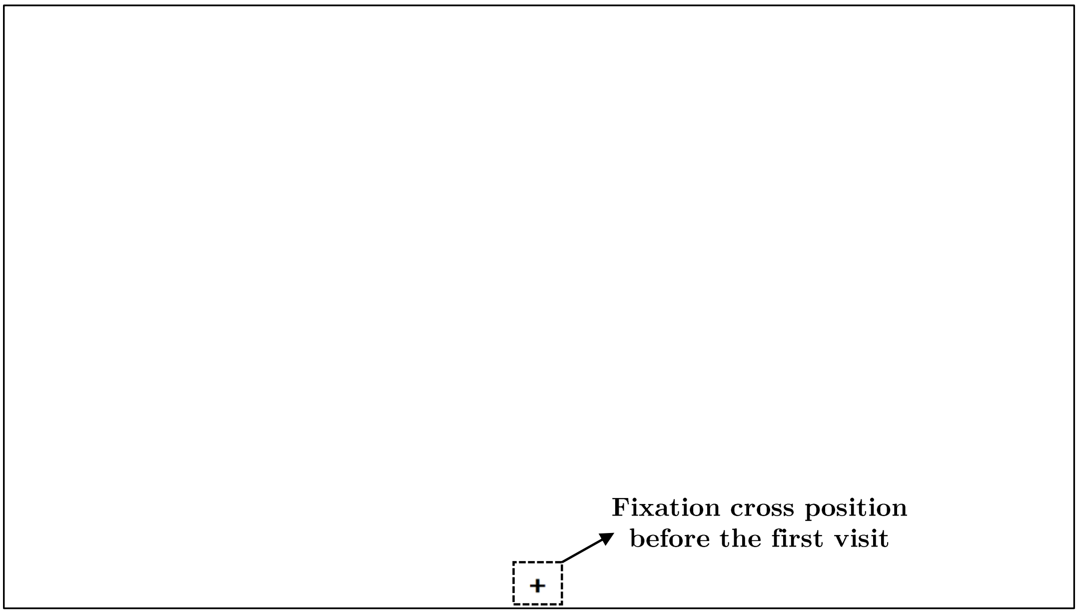


Figure E.9.: The fixation cross position before first visit in Study V.

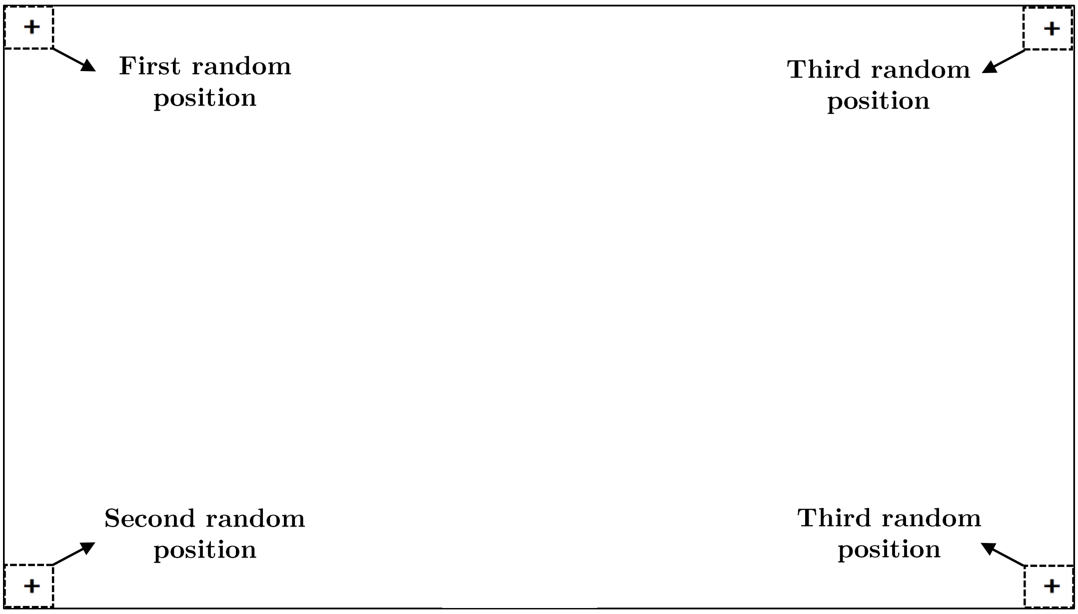


Figure E.10.: The fixation cross position after gaze-based TRS in Study V.

Figure E.11.: The control condition in Study V in which users do not receive any gaze-based TRS.

E.2. Survey Items

Controls	Items	Measure
Perceived Usefulness	• "Using this feedback would improve my performance to resume the exploration task after answering the email.“ • "Using this feedback would increase my productivity on resuming the interrupted data exploration task.“ • "Using this feedback would make it easier to resume my interrupted data exploration task.“ • "I would find this feedback useful in resuming the interrupted exploration task."	Davis (1989) Likert Scale 1 to 7
Easy to Use	• "Learning to operate this attention feedback would be easy for me.“ • "I would find this attention feedback easy to use.“ • "It would be easy to become skillful at using this attention feedback."	Davis (1989) Likert Scale 1 to 7
Self-Awareness	• "Due to this attention feedback, I'm conscious of my data exploration strategy.“ • "Due to this attention feedback, I'm reflective of my data exploration strategy.“ • "Due to this attention feedback, I'm aware of my data exploration strategy."	Twenge et al. (2007) Likert Scale 1 to 7
Behavioral Intention	• "I intend to use this feedback in the future to support me in resuming my interrupted task.“ • "I predict I would use this feedback in the future to support me in resuming my interrupted task.“ • "I plan to use this feedback in the future to support me in resuming my interrupted task."	Venkatesh et al. (2003) Likert Scale 1 to 7

Table E.1.: Items used in the final survey of Study V.

E.3. Further Analysis

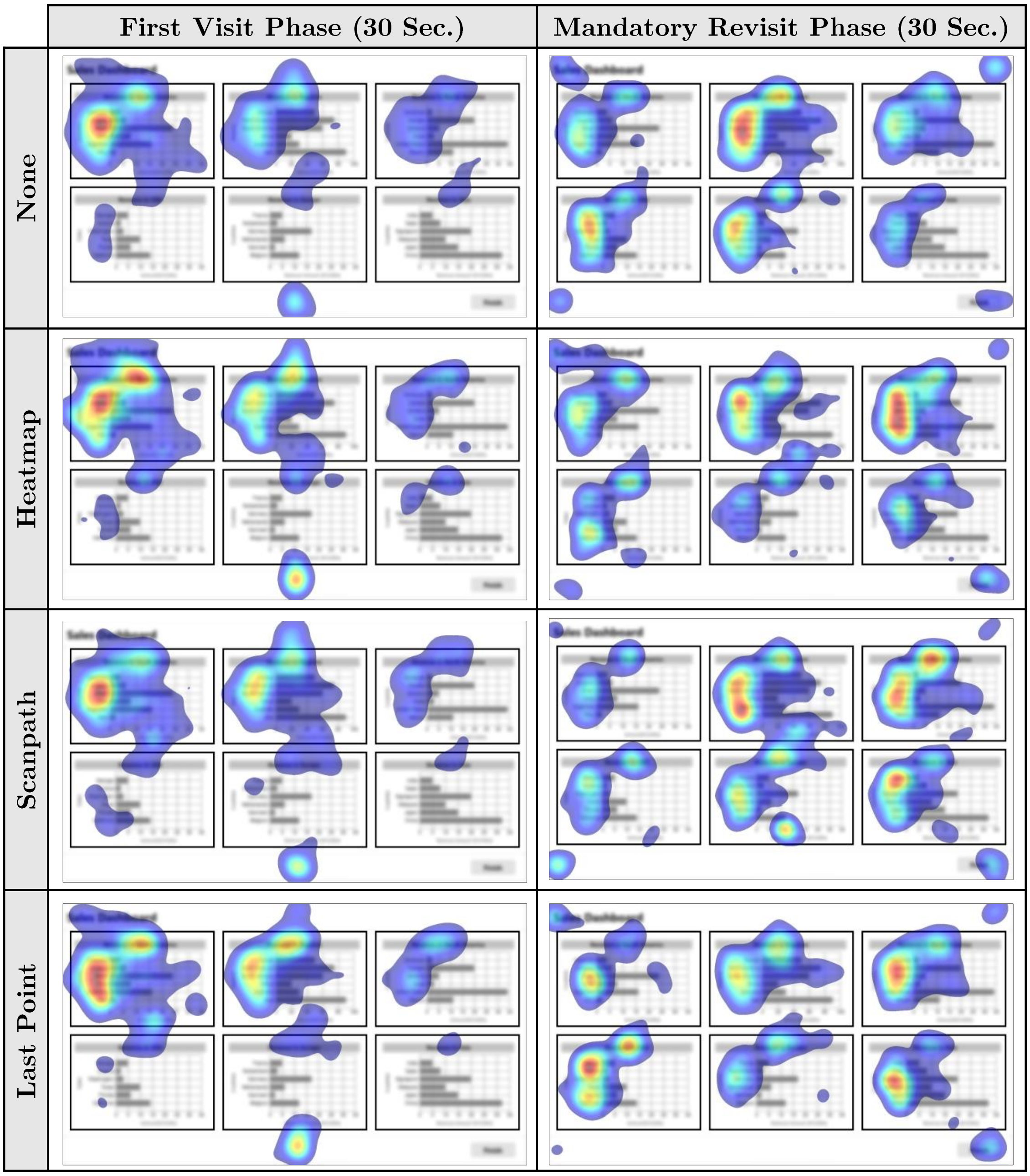


Figure E.12.: The heatmaps of users with low WMC in first visit and mandatory revisit phases of the experiment in Study V.

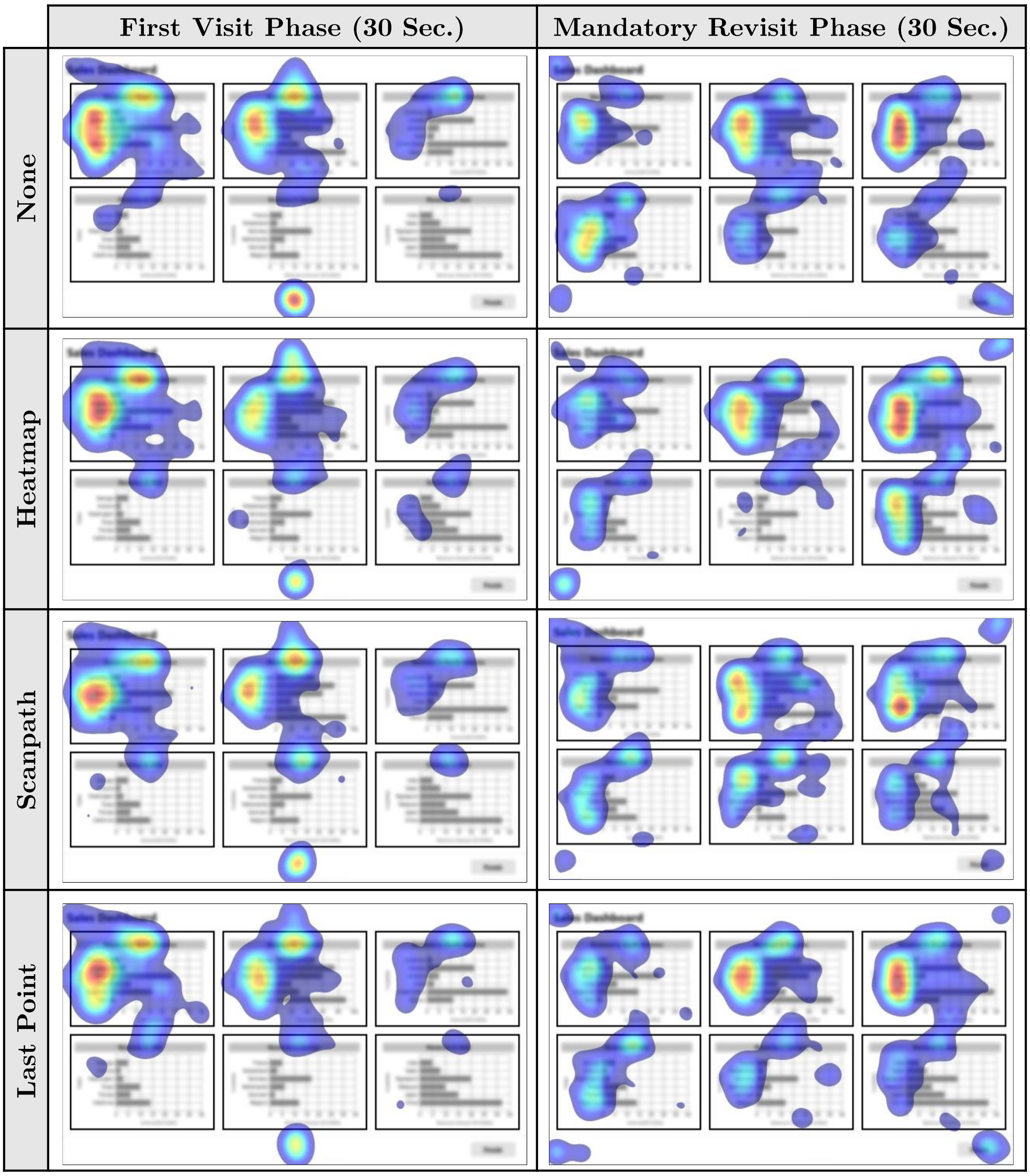


Figure E.13.: The heatmaps of users with high WMC in first visit and mandatory revisit phases of the experiment in Study V.

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List of Publications

Publications Related to this Thesis

Toreini, P., and Morana, S. (2017). Designing Attention-aware Business Intelligence and Analytics Dashboards. In *Research in Progress Proceedings of the 12th International Conference on Design Science Research in Information Systems and Technology (DESRIST)* (pp. 64–72). Karlsruhe, Germany.

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Langner, M., Toreini, P., and Maedche, A. (in press). AttentionBoard: A Quantified-Self Dashboard for Enhancing Attention Management with Eye-Tracking. In *Davis F., Riedl R., vom Brocke J., Léger PM., Randolph A., Fischer T. (eds) Information Systems and Neuroscience (NeuroIS Retreat 2020)*. Virtual Conference.

Publications Under Review or Working Papers

Toreini, P., Maedche, A., Langner, M., Morana, S., and Vogel, T. (2020a). Designing Attentive Information Dashboards. *Under review in the Journal of the Association for Information Systems (JAIS).*

Toreini, P., and Maedche, A. (2020). Eye-based Interactive Intelligent Systems: State-of-the-Art and Future Direction. *Working Paper.*

Toreini, P., Langner, M., and Maedche, A. (2020c). Gaze-based Task Resumption Support - The Role of Working Memory Capacity. *Working Paper.*

Eidesstattliche Versicherung

gemäß § 6 Abs. 1 Ziff. 4 der Promotionsordnung des Karlsruher Instituts für Technologie für die Fakultät für Wirtschaftswissenschaften

1. Bei der eingereichten Dissertation zu dem Thema „*Designing Attentive Information Dashboards with Eye Tracking Technology*“ handelt es sich um meine eigenständig erbrachte Leistung.

2. Ich habe nur die angegebenen Quellen und Hilfsmittel benutzt und mich keiner unzulässigen Hilfe Dritter bedient. Insbesondere habe ich wörtlich oder sinngemäß aus anderen Werken übernommene Inhalte als solche kenntlich gemacht.

3. Die Arbeit oder Teile davon habe ich bislang nicht an einer Hochschule des In- oder Auslands als Bestandteil einer Prüfungs- oder Qualifikationsleistung vorgelegt.

4. Die Richtigkeit der vorstehenden Erklärungen bestätige ich.

5. Die Bedeutung der eidesstattlichen Versicherung und die strafrechtlichen Folgen einer unrichtigen oder unvollständigen eidesstattlichen Versicherung sind mir bekannt. Ich versichere an Eides statt, dass ich nach bestem Wissen die reine Wahrheit erklärt und nichts verschwiegen habe.

Karlsruhe, den

Peyman Toreini