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Abstract:

Eye-trackers provide continuous information on individuals' gaze behavior. Due to the increasing popularity of eye-tracking in the information systems (IS) field, we reviewed how past research has used eye-tracking to inform future research. Accordingly, we conducted a literature review to describe the use of eye-tracking in IS research based on a sample of 113 empirical papers published since 2008 in IS journals and conference proceedings. Specifically, we examined the methodologies and experimental settings used in eye-tracking IS research and how eye-tracking can be used to inform the IS field. We found that IS research that used eye-tracking varies in its methodological and theoretical complexity. Research on pattern analysis shows promise since such research develops a broader range of analysis methodologies. The potential of eye-tracking remains unfulfilled in the IS field since past research has mostly focused on attention-related constructs and used fixation count metrics on desktop computers. We call for researchers to utilize eye-tracking more broadly in IS research by extending the type of metrics they use, the analyses they perform, and the constructs they investigate.

Keywords: Eye-tracking, NeuroIS, Information Systems, Literature Review

Soussan Djamasbi was the accepting senior editor for this paper.

1 Introduction

Eye-trackers are affordable and accessible tools that measure eye position and movement with high temporal precision via using an unobtrusive method based on the cornea's reflection (Duchowski, 2007; Etco et al., 2017). Information systems (IS) researchers have used eye-tracking tools to measure what people attend to during human-computer interaction, and they constitute one among the many tools that the Neuro-information systems (NeuroIS) field uses to collect neurophysiological data on participants (Riedl & Léger, 2015). Both scientists and practitioners use eye-trackers. Due to their rapidly diminishing cost, we expect their use to grow in IS research.

During the last decade, 31.5 percent of NeuroIS research has used or discussed eye-tracking (Riedl et al., 2020). To inform and optimize future research, it is important to review to what extent and for what purposes researchers have used eye-tracking thus far.

Hence, in this study, we describe how research during the last decade has used eye-tracking. Specifically, we address the following research questions (RQ):

> **RQ1**: What methodologies have been used in eye-tracking IS research?
>
> **RQ2**: How does eye-tracking inform IS research?

The first research question (RQ1) concerns the role that eye-tracking has played in the IS field. To answer this question, we examined the experimental settings and the type of analyses that researchers have performed. To provide insight into current research practices, we also examined the type of metrics they used. To answer the second research question (RQ2), we examined the role and value of eye-tracking in IS research. Thus, we examined the constructs that eye-tracking IS research has investigated and how eye-tracking has informed IS research.

We conducted this review to learn from previous publications, identify current practices, as well as shed light on research gaps and potential areas for improvement. We examine both eye-tracking's limitations and benefits. We contribute to the literature by providing descriptive statistics on how IS studies have used eye-tracking and qualitatively analyzed the investigated constructs. We also summarize the theoretical background of eye-tracking and provide some guidelines for future research.

This paper proceeds as follows. In Section 2, we explain how we selected the papers and coded them. In Section 3, we focus on what key metrics these papers used and which constructs they investigated. In Section 4, we focus on the most relevant findings and aggregate them in an understandable and actionable fashion to stimulate and guide future research. Finally, in Section 5, we conclude the paper.

2 Methodology

We conducted a keyword search on the Web of Science using the keywords "eye" OR "eye track*" OR "eye-track*" in journals with an IS and human-computer interaction (HCI) orientation, which included the basket of eight (AIS) and conference proceedings. We selected the outlets from a group of journals that commonly publish NeuroIS research (Riedl et al., 2020). We list the outlets that we considered in the search phase in Appendix A.

From the Web of Science search results, we selected only fully empirical studies that collected eye-tracking data and that pertained to the IS or HCI field. We excluded studies that tested eye-tracking tools as input devices for developing IT artifacts that used eye-tracking or that used it for medical training. Moreover, we did not include publications relevant to neuroscientific analysis techniques, engineering, or medicine. Finally, we excluded papers that did not have a results section. The final sample comprised 113 publications with a publication date that ranged from 2007 to 2020. We list all outlets we used in the final sample in Appendix B and all studies we consulted for this review in Appendix C.

We collected general information on the studies such as their authors, publication year, title, publication type, and the journal or conference proceedings that published them. We then coded each paper on multiple dimensions. We indicated each study's topic, how many participants the study had, the type of experimental design, the independent and dependent variables that it examined, and the eye-tracking metrics that it used.

3 Results

3.1 RQ1: What Methodologies Does Eye-tracking IS Research Use?

We analyzed 113 papers (92 journal publications and 21 conference papers). Our review revealed that publications reporting results from eye-tracking research have begun to appear in high-ranking journals such as *MIS Quarterly* (3 articles) and *Information Systems Research* (1 article). The journal *Computers in Human Behavior* seems the most fruitful avenue for researchers who want to publish eye-tracking studies given it has published 43 eye-tracking studies.

3.1.1 Experimental Design

We examined experimental procedures that eye-tracking research has used. First, we considered experimental design and coded papers based on whether they used a within, a between, or a mixed design (see Table 1) because eye movement depends on many individual factors. To control for these factors, researchers can find it worthwhile to have a within-subject design (Riedl & Léger, 2015).

Second, we collected data on how many participants each study contained. When a paper reports results from multiple experiments, we report the average number of participants in these experiments. Figure 1 shows the distribution of the number of participants by experimental design, and Table 2 presents the major descriptive statistics.

We found that 50 studies used a between-subject design, 46 used a within-subject design, and 17 used a mixed design. Just as in any other type of experimental research, between-subject studies with eye-tracking require more participants than within-subject studies to obtain significant results. We observe that most papers that used a within-subject design had less than 40 participants, while most papers that used a between-subject design had less than 60 participants (see Table 2). These numbers concur with the average number of participants in NeuroIS studies in general (Riedl et al., 2020).

We found that the number of participants did not correlate with the constructs or the metrics in the papers. For example, both a between-subject publication with 451 participants (Lo et al., 2014) and a within-subject study with 17 participants (Pak & Zhou, 2013) used fixation duration. We take a closer look at the metrics in Section 3.

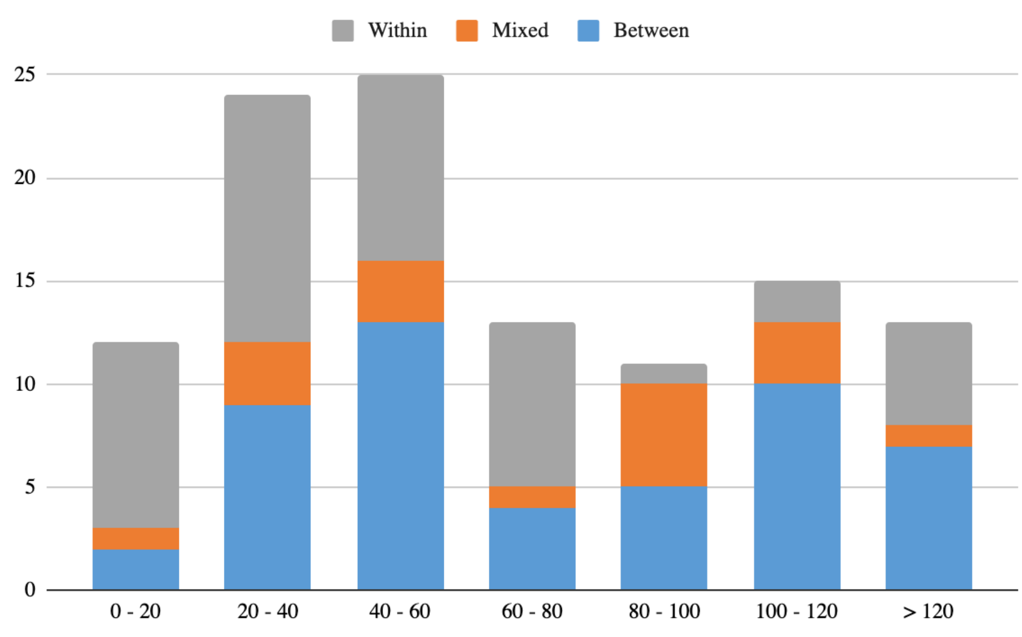

Figure 1. Distribution of the Number of Participants in the Studies Classified by Experimental Design

Table 2. Number of Research Participants per Design Type

Type of study	Average	Minimum	Maximum	Std. Dev.	Median
Between	79.89	14.50	451.00	64.65	60.00
Mixed	70.94	16.00	156.00	37.06	80.00
Within	54.77	5.00	197.00	42.78	41.50
Total	**68.32**	**5.00**	**451.00**	**54.18**	**56.00**

3.1.2 Metrics

Eye-tracking metrics constitute measurements that correlate with the human visual system. They relate to how the nervous system receives visual information and processes it. Eye movements come in two types: fixations and saccades. Fixations occur when the eye remains relatively stable for a period between 200 and 300ms, while saccades occur between fixations. Given that saccades last only about 40ms (Rayner, 1998), they have a more rapid nature than fixations. In addition, pupil diameter provides information on an individual's cognitive state (Sharafi et al., 2015).

To capture these aspects of human vision, eye-tracking devices obtain information related to fixations, saccades, and pupil dilation. They record participants' gaze to determine the specific areas that viewers look at (called areas of interest (AOI)). In addition, they calculate fixation count (i.e., to determine how often a specific item is viewed) and dwell time (i.e., the total amount of time spent looking at a specific area). By using heatmaps, it then becomes possible to precisely represent what participants look at the most (see Figure 2). Analyzing heatmaps provides qualitative information to researchers on the areas that participants focused on most during their visual experience. Therefore, unlike the data obtained from a quantitative analysis based on fixation counts, fixation duration, and pupil dilation, one cannot compare the data in heatmaps statistically.

Figure 2. Heat Map from Djamasbi et al. (2014)

Finally, when one combines gaze data with temporal markers, one can obtain a "scanpath", which shows how individuals' gaze moves spatially and temporally. One can represent scanpath data visually and qualitatively but can also aggregate and compile it into quantitative measures that one can statistically analyze and compare to highlight differences in viewing patterns.

Researchers can also arrange, combine, and compile these primary metrics—fixations, saccades, scan-paths, and pupil diameters—into aggregated or calculated metrics such as the time to first fixation or the percentage of fixation on an area. Accordingly, we classified the papers that we reviewed according to the primary type of metrics used (see Table 3).

Table 3. Primary Eye-tracking Metrics

Metric	Definition
Fixation count (FC)	The total number of fixations for each AOI
Fixation duration (FD)	The sum of the durations of all fixations on a specific AOI

Table 3. Primary Eye-tracking Metrics

Fixation sequence (FS)	The gaze sequence when both spatial and temporal information on the gaze of participants is used (also referred to as "scan-path analysis")
Time to fixation (TTF)	The time it takes to fixate on a specific area (also referred to as "time to first fixation")
Pupil dilation (PD)	The measure of the pupil's diameter
Heatmaps (HM)	The qualitative visual representation of the AOI aggregated by participants or by treatment groups

The papers in our sample used an average of 2.05 measures. We found that FC and FD were the most frequently used measures: they appeared in 71 (63%) and 89 (79%) papers, respectively (see Table 4). Furthermore, 15 papers used FS, 23 papers used TTF (20%), 13 papers used PD (12%), and 29 papers used heatmaps to make sense of or complement other metrics (26%).

Table 4. Metrics Used in Eye-Tracking-Based IS Research

Metrics	HM	FD	FC	TTF	PD	FS	Total
Number of publications	29	89	71	23	13	15	113
Percentage of the sample	25%	78%	62%	20%	11%	13%	100%

Beyond the number of papers that used each metric, we also mapped their evolution over time (see Figure 3). FC and FD have seen consistent use over the years, while PD and FS appeared more recently except for one study in 2008. Advancements in machine learning algorithms and research on scanpath analyses seem to have resulted in more studies that used the fixation sequence metric. We explore how the papers used these specific metrics to represent IS constructs in the following subsections.

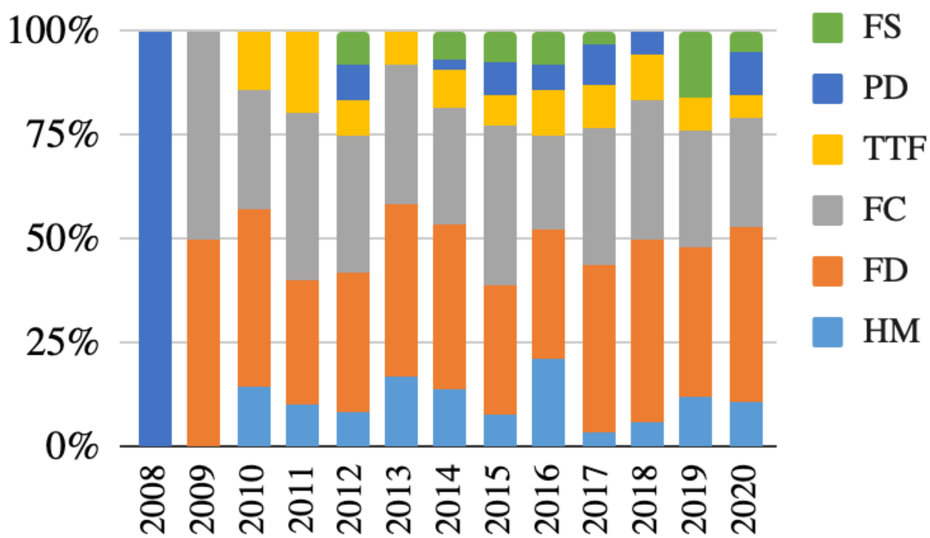

Figure 3. Percentage of Metrics Used in Eye-tracking IS Research per Year

3.2 RQ2: How Can Eye-tracking Inform IS Research

In this section, we report on whether studies used eye-tracking as an independent variable (IV) or as a dependent variable (DV). We also explore the theoretical and methodological underpinnings of eye-tracking.

One can address many research questions using measures from eye-tracking instruments. We found that 78 percent of the studies involving eye-tracking measures used them as DVs. Only two empirical papers in our sample used eye-tracking as a mediator (Reani et al., 2019; Yang, 2014). Only one paper used eye-tracking as a triangulation tool but only to analyze face-reading measures by identifying the moment when individuals began fixating on an element (Fehrenbacher, 2017). We next discuss how papers used eye-tracking measures as IVs and the inferences that can be made using these measures.

3.2.1 Eye-tracking Measures as Independent Variables (IVs)

Twenty-three studies in our sample used eye-tracking to predict comprehension, behavior, or perception (see Figure 4). Research has shown that eye-tracking metrics predict individual accuracy or problem-solving performance. For example, performance correlates with a longer fixation time (Djamasbi et al., 2012a; Petrusel & Mendling, 2013), with reasoning accuracy, with gaze behavior (Reani et al., 2019), with intention to buy, and with fixation duration (Yang & Lin, 2014). Moreover, machine learning and clustering analyses from composite measures of eye-tracking metrics can predict the task that participants are performing (Cole et al., 2015).

Whether they focus on reinforcing theory-based hypotheses, providing empirical evidence to support relationships, or determining a topic’s suitability, exploratory studies represent an exciting avenue for eye-tracking research. For example, since fixation patterns on a page can predict visual appeal perceptions (Djamasbi et al., 2011), researchers have an empirical grounding for studies that involve questions related to this construct (Djamasbi et al., 2014).

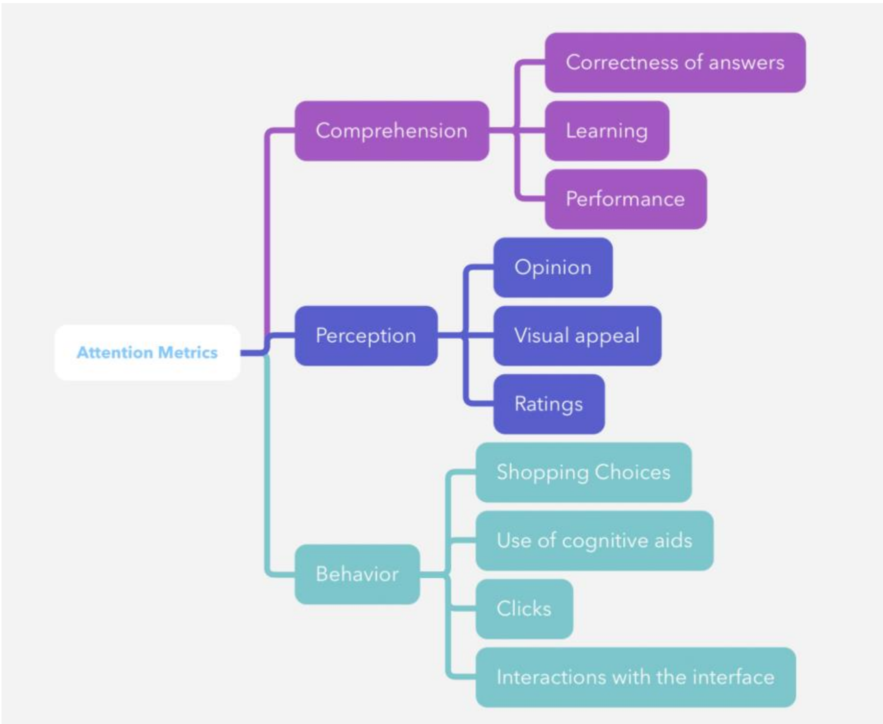

Figure 4. Predictions Based on Attention-related Metrics in IS Research

However, gaze-behavior patterns do not always correlate with outcomes, and using eye-tracking metrics to anticipate behaviors has some limitations. For example, researchers have found no statistical relationship between gaze-behavior patterns and willingness to share information (Fehrenbacher & Tracy, 2016) or between gaze-behavior patterns and how individuals evaluate online articles (Steinfeld et al., 2016).

3.2.2 Eye-tracking Measures as Dependent Variables (DVs)

Studies using eye-tracking focused on 1) the effect of individual qualities (21.59%), 2) design features (50%), 3) task characteristics (25%), or 4) device attributes (3.41%) on eye-movement behavior (see Appendix D).

In this section, we report on the constructs of interest that IS research has investigated with eye-tracking. We start with more simple studies both in terms of theory development and measurement choices (e.g., studies that use raw data to correlate with specific behaviors without linking their metrics to specific theories). We then discuss papers that adopt more complex theory-based explanations and more intricate methodological tools (e.g., studies using qualitative investigation and machine-learning techniques).

Attention in IS research based on eye tracking: One can use eye-movement data such as the fixation duration and fixation time as proxies for attention. In some studies, researchers reported raw metrics without linking them to higher-level theories in their hypotheses or analyses. These studies used eye-tracking 1) to compare the effect that design choices have on viewing and fixation times (Cyr et al., 2009; Djamasbi et al., 2012a; Pantazos & Vatrapu, 2016), 2) to examine the difference between individual characteristics such as how a novice or an expert accomplishes certain tasks (Dogusoy-Taylan & Cagiltay, 2014), 3) to explore the role that deception plays in eye-gazing behavior (Pak & Zhou, 2013), or 4) to investigate the relation between different task types and eye behavior (Pinggera et al., 2013).

Some researchers supported their quantitative reports with heatmaps and qualitative interpretations to help explain the observed behavior (Djamasbi et al., 2012c). Indeed, when one needs to triangulate data, eye-tracking can be beneficial since it can complement and refine other measures such as interviews and questionnaires to obtain insight (Cyr et al., 2009; Djamasbi et al., 2012a; Pinggera et al., 2013; Steinfeld, 2016) while at the same time providing empirical evidence to support an association between eye movement and other constructs (Djamasbi et al., 2014).

However, fixations and saccades measure visual attention (Henderson, 1993), and 36 percent of the papers in our sample used eye-tracking metrics as proxies for attention. In addition to comparing the extent to which individuals paid attention to different design choices or device types, eye-tracking can investigate how different task types can impact users' attention (see Table 5).

Table 5. Attention-related Studies

Level of interest	Conditions	Source
Design level	Presence vs. absence of advertisement	Ahn et al. (2018)
	Consumers' reviews vs. editorial reviews	Amblee et al. (2017)
	Lower-level (motion) vs. higher-level (faces) visual cues	Brasel & Gips (2017)
	Barrage video VS non-barrage video	Chen et al. (2019)
	Animated VS non-animated banner	Hamborg et al. (2012)
	Region of interest in displayed pictures	Ho (2014
	Ad position and content position	Huang (2018)
	Animated vs. non-animated content	Lee & Ahn (2012)
	Format and speed of animation	Li et al. (2016)
	Icon composition and background	Lin et al. (2016)
	Shape of banner ads	Liu et al. (2018)
	Dashboard features	Nadj et al. (2020)
	Signaled VS non signaled multimedia materials	Ozcelik et al. (2010)
	Complexity of web page	Still (2018)
	Type and intensity of model's smile	Wang et al. (2017)
	Star ratings	Willems et al. (2019)
	Nature of dynamic content	Jay et al. (2013)
	Text only vs. text and images content	Meppelink & Bol (2015)
Individual	Friendship level (part of a group vs. not in the group)	Wang & Hung (2019)
	Friend's referral	Windels et al. (2018)
	Expertise	Meservy et al. (2014)
	Content preference / personal interests	Vraga et al. (2019)
	Lonely vs. normal viewers	Chen et al. (2019)

Table 5. Attention-related Studies

Task	Cognitive demand	Bang & Wojdynski (2016)
	Different purchasing tasks	Cortinas et al. (2019)
	Experiencing vs. observing failure	Jensen et al. (2016)
	Products, prices, and sales features	Linfeng et al. (2013)
	Time pressure	Liu et al. (2017)
	Products vs. experience review	Luan et al. (2016)
	Time scarcity, social popularity	Mou & Shin (2018)
	Task complexity, website complexity	Wang et al. (2014a)
Device	Computer vs. mobile devices	Dunaway et al. (2018)

How individuals allocate attention has particular relevance for IS research on artifact design, IS use, techno-stress, neuro-adaptive systems, e-commerce, and advertising since eye-tracking can precisely capture unconscious and continuous processes that one cannot measure objectively through perceptual measures such as surveys and questionnaires (Riedl & Léger, 2016). Eye-tracking can identify regularities in visual attention allocation that are less susceptible to bias than self-report data (Dimoka et al., 2012) and, therefore, can inform how visual attention varies depending on information systems choices. Indeed, research found that individuals have attention renewal and attention adjustment that can be triggered by design choices (Ahn et al., 2018). In attentional research, eye-tracking metrics play a major role in distinguishing between exposure and attention (Lee & Ahn, 2012). Even though exposure is a prerequisite for attention, one cannot use them interchangeably. By augmenting the methodology of their study with eye-tracking metrics, researchers can better ensure that their measurement of constructs (e.g., attention) is valid and that other competing constructs (e.g., exposure) or biases do not confound their results.

Under this category, we also coded constructs that relate closely to attention based on the authors' definition. For example, Meservy et al. (2014) used gaze patterns as a proxy for *elaboration*, which they defined as "the degree to which the knowledge seeker systematically examines the content of the knowledge to determine its value" (Meservy et al., 2014, p. 19). This construct takes into consideration the systematicity of attention to specific content.

Studying patterns with eye-tracking: IS research has used eye-tracking to investigate different pattern types: information-search patterns (Etco et al., 2017; Huang & Kuo, 2012), processing patterns (Liu et al., 2011; Scott & Hand, 2016), reading patterns (Andaloussi et al., 2019), and usage patterns (Eckhardt et al., 2013). Even though researchers have used different terms such as reading, usage, or processing patterns, this category focuses on the relationship between different areas. More specifically, researchers have primarily used pattern analyses to understand how individuals move between areas of interest.

In their study on the role that external pressure plays in patterns of use, Eckhardt et al. (2013, p. 2) conceptually defined usage patterns as "users' regions of interest (ROI) and the number of views on each ROI". When reading this definition, one could think that the authors focused purely on studying attention and what users looked at in terms of fixation duration. However, in operationalizing usage patterns, they used not only ROI (or AOI) and the number of views but also fixation distribution using a Gaussian mixture model. They also automatically derived the AOIs using an expectation-maximization algorithm. Thus, this example illustrates that pattern analyses require more advanced techniques than just descriptive statistics used in attention research. Pattern analysis is also concerned with uncovering probabilities of looking at a specific area, and more specifically, the sequencing of these probabilities.

Andaloussi et al. (2019) studied the effect of individuals' backgrounds on reading patterns and took the same methodological approach as Eckhardt et al. (2013): they computed the probability of transitions between AOIs. However, they did not derive AOIs from an algorithm but individually defined them based on the AOIs related to their research question. They also provide an interesting representation of the frequency of transition between AOIs by using attention maps (see Figure 5). Such a representation shows the different AOIs and the probability that individuals in each treatment will move from one area to another.

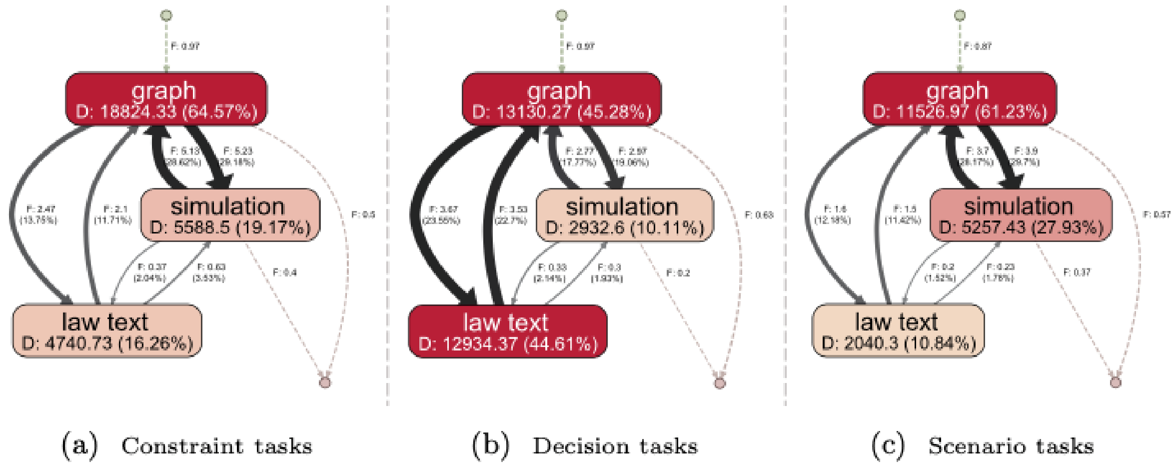

Figure 5. Example of Attention Maps (Andaloussi et al., 2019)

Similarly, information search patterns have been examined by calculating the proportion of the difference between within-attributes pairs and within-alternative pairs (Fadel et al., 2015; Huang & Kuo, 2012). This method does not use transition probabilities but involves more complexity than using only fixation duration. Indeed, it encompasses the need to look at a specific area compared to looking at external areas and involves developing an equation that corresponds to the patterns investigated.

Eye-tracking can also provide information on other types of patterns, such as individuals' thought patterns (Liu et al., 2011; Scott & Hand, 2016). One alternative way to use eye-tracking to investigate patterns, beyond mathematical or machine learning techniques that involve the probability that one will switch from certain areas to others, is to combine quantitative analysis of fixation duration and counts with a qualitative analysis of the scan paths (Liu et al., 2011, p. 2413).

Among its interesting characteristics, pattern analysis research needs more advanced mathematical tools than other types of eye-tracking research. In other words, such research cannot rely on descriptive statistics and simple comparisons alone. However, pattern analysis eye-tracking research would benefit from combining advanced mathematical and analytic tools (e.g., machine learning, classification algorithms) with qualitative data (e.g., heatmaps).

Pupillary-related constructs: 12 papers in our sample used eye-tracking metrics to measure cognitive load or arousal. Table 6 summarizes the questions that are investigated with pupillary-related constructs. We identified arousal as the most common construct associated with the pupil's response. These studies used the eye-mind hypothesis (i.e., the idea that eye-tracking results can reveal a user's underlying cognitive processes) as their theoretical background (Chen et al., 2011, as cited in Zhou et al., 2015). When studying constructs related to physiological activity, we need to look beyond fixation and gaze measurements by examining participants' pupil diameter. Pupillary changes are associated with emotional arousal and can provide studies with continuous and objective measures of arousal during a task rather than obtaining perceptual arousal measures at the end of a task. Research has also linked cognitive load to pupil dilation during decision-making (Fehrenbacher & Djamasbi, 2017; Simpson & Hale, 2016). Having access to non-invasive measures, such as pupil diameter from an eye-tracker, can complement perceptual ways to measure cognitive load (e.g., NASA-TLX) (Hart & Staveland, 1988).

Table 6. Questions Investigated with Pupillary Measures

Research question (eye-tracking related construct/metrics in bold)	Source
How does **mental workload** change during the execution of goal-directed tasks?	Bailey & Iqbal (2008)
How does task demand affect a user's **pupil response**?	Fehrenbacher & Djamasbi (2017), Shojaeizadeh et al. (2017)
How does experiencing versus observing a failure in a learning situation impact the **arousal** level of the participant?	Jensen et al. (2016)

Table 6. Questions Investigated with Pupillary Measures

Are there differences in terms of **engagement, cognitive processing**, and observation of information found on social commerce websites when making purchase-related decisions?	Mikalef et al. (2020)
What is the influence of online news and clickbait headlines on online users' **emotional arousal**?	Pengnate (2016)
What is the effect of web atmospheric cues, mainly vividness and interactivity, on users' **emotional responses**?	Sheng & Joginapelly (2012)
Is risk perception correlated with the **pupil's diameter**?	Tzafilkou & Protogeros (2017)
How a model's eye gaze direction influences consumers' **arousal**?	Wang et al. (2018)
How the presence of a human image on B2C websites affects consumers' **arousal**?	Wang et al. (2014b)
How does classical and expressive aesthetics influence users' **arousal**?	Ye et al. (2020)
How do various levels of difficulty of decision-making impact users' **pupillary response**?	Zhou et al. (2015)

4 Discussion

4.1 The Value of Eye-tracking in IS Research

In this section, we highlight specific publications to illustrate the value of eye-tracking at different levels of analysis. First, researchers can report raw eye-tracking data to complement research findings that they investigated through other means. For example, Steinfeld et al. (2016) looked at how users read privacy policy when they received it by default versus by their own choice. They found a link between the duration that users stayed on the privacy policy and how well they understood the consequences of the policy. With their eye-tracking measures, they could infer which paragraph participants found the most important and, thus, understand how users read the policies. In this case, eye-tracking provided additional information regarding how users spent their time on the privacy policies.

Second, empirical research can be helpful in extending the value of eye-tracking in predicting perceptual or cognitive measures. Djamasbi et al. (2014) found that fixation duration on a website's main image can predict its visual appeal. If we can consistently use eye-tracking to predict specific perceptual variables, it can become a valuable tool to reduce questionnaire length in laboratory experiments and to help researchers assess the real-time appeal while navigating without the invasiveness or bias associated with other methods.

Third, researchers can also use eye-tracking as a non-invasive way to measure behavioral constructs such as habituation (Anderson et al., 2016a, 2016b). The eye movement-based memory effect states that individuals have different eye movements depending on whether they have previously seen a specific stimulus. This neurological framework gives researchers a way to use eye-tracking to measure habituation. This creative way to mobilize eye-tracking, beyond using it as a proxy for attention, shows the value of exploring biological, neurological, and physiological research that is linked to IS constructs.

Fourth, researchers can also use eye-tracking data as a first step toward building neuro-adaptive models by discovering the links between patterns of fixation and information processing in the brain (Weber et al., 2016). Patterns of fixation can then be used for real-time detection of users' activity. Such research assumes that eye movement patterns relate to higher-level constructs such as information processing or problem understanding. Hence, the goal is to uncover specific patterns and link them to higher-level constructs such as problem understanding, method finding, syntactic validation, and semantic validation (Weber et al., 2016).

Lastly, eye-tracking is a powerful tool when used in triangulation with other measures. For example, Leuthold et al. (2011) used eye-tracking metrics as proxies for performance by looking at the number of eye fixations before the first click, the time needed for the first click, and information correctness. By collecting eye-tracking, mouse clicks, and other behavior measures concurrently, the analysis can provide deep and rich insight that cannot be obtained with single measures.

4.2 Recommendations for Future Research

4.2.1 Hardware and Software Considerations

We found that 97 percent of papers in our sample used desktop computer eye-tracking devices. The effect of device type is largely understudied. Only three studies looked at how the device type impacted eye movement patterns and task completion. As individuals increasingly use mobile technology and as its impact on individuals and organizations increases, we need to expand eye-tracking research beyond desktop computers. Tools are currently being developed to help address this issue. For example, Pupil, an open-source mobile eye-tracking solution, provides a gaze accuracy of 0.60° and can record both pupil and gaze data. As of May 2023, the Pupil website lists 586 publications across all fields that have used the solution (pupil-labs.com/publications/) since its development in 2014 (Kassner et al., 2014). The IS field could use this and similar tools to study how individuals use their smartphones, tablets, or even voice-activated systems. For example, we could study if a user's gaze can inform us of the user's level of frustration as well as cognitive load.

Desktop trackers are non-intrusive devices that detect eye movement using infrared technology. However, more intrusive headband-mounted eye-trackers also exist (Sharafi et al., 2015). Head-mounted devices record pupil and corneal reflection at different sampling frequencies (30 to 400 Hz depending on the device) and accuracy (Cognolato et al., 2018). These devices also record the scene in front of the user, which allows for more diverse research environments, compared to desktop eye-trackers, which can only record a computer screen. Ultimately, the eye-tracking hardware that researchers choose depends on the research question and the problem they investigate. IS research could benefit from considering mobile eye-tracking as a tool that can record behaviors in a natural environment. Mobile eye-tracking continues to evolve and has been used for various research projects such as recognizing document types (Kunze et al., 2013), examining pilots' gaze in the cockpit (Weibel et al., 2012), analyzing museum visitors' visual perception (Yi et al., 2020), and studying elite baseball players' eye and head movements during baseball games (Kishita et al., 2020).

Little IS research has used mobile tracking partly due to the difficulty of obtaining the same cost-efficiency ratio as desktop tracking since mobile use involves variations in distance, view angle, and light conditions, which makes accuracy significantly more difficult to achieve. However, recent advances in machine learning technologies have shown that one can use personal smartphone cameras to conduct eye-tracking research at an accuracy level that one would normally expect from high-end devices (Valliappan et al., 2020). Such technological advancement shows great promise for conducting eye-tracking IS research at a low cost, with many participants, and in a natural environment.

In addition to hardware, researchers also have choices to make regarding the software they use to analyze the millions of eye-tracking data points that they collect for each participant. The options available depend on the hardware chosen since some popular software such as Tobii Pro only work when one collects data with Tobii devices, whereas others such as SmartGaze or iMotions can analyze data collected from different devices.

4.2.2 Moving Beyond Descriptive Analysis and Heatmaps: Visualizations and Analysis Options

Many studies in our sample used quantitative analyses based on frequency and duration to extract insights from the data and answer research questions. Sometimes, they complemented these analyses with qualitative visualizations, such as heatmaps, to provide context for the findings. However, the IS field has yet to use many scanpath- or AOI-based visualization options (Blascheck et al., 2017). Table 7 shows some of those visualization methods.

Table 7. Visualization Options for Eye-tracking Data

Method / source	What does it represent	Why use it	Source with examples
Gaze stripes	Sequence of gaze point images oriented along a horizontal timeline	• No need to define AOIs • Represent spatiotemporal data • Suited for dynamic stimuli • Can be enriched with annotation to provide context	Kurzhals et al. (2016)

Space-time cube	Dynamic and interactive three-dimensional view combining time and space	• Represent spatiotemporal data • Identify patterns of multiple participants • Can be enriched with analytical functions (moveable base map, spatial zoom, attribute filter, temporal zoom)	Li et al. (2010)
Saccade plot	Gaze frequencies as a heat map and saccade as color-coded triangular matrices	• Represent spatiotemporal data • Include saccades and fixations	Burch et al. (2014)
Fixation distance plot	Fixation sequences on a horizontal line color-coded with different thick circles	• Can be augmented with saccadic information • Less visual clutter • Represent spatiotemporal data	Burch (2018)

With a spatiotemporal approach, there are more quantitative options available than are displayed in our sample. For example, with static stimuli, it is possible to 1) calculate the similarity or dissimilarity of scanpaths, 2) calculate the probability that users will transition from one area to another, 3) detect specific patterns, or 4) identify specific patterns (Eraslan et al., 2016). To perform scanpath analyses, IS researchers can use techniques that rely on machine learning or specific algorithms that researchers in other academic fields have used (e.g., string-edit algorithm, Needleman and Wunsch algorithm, Markov models, sequential pattern mining). We refer readers to Eraslan et al. (2016) for a description of available techniques.

4.2.3 Increasing the Complexity of Analyses

When consolidating findings related to fixations and saccades, we see emerging patterns in theoretical and methodological complexity, regardless of whether researchers used these measures as proxies for attentional constructs or processing patterns (see Figure 6). Measures of eye movement have been used to compare the different reactions to stimuli, but are sometimes used without a theoretical basis. In these cases, researchers have not linked their measures to any behavioral, cognitive, or emotional construct but rather only compared raw fixation time to show differences. Eye-tracking measures are useful for exploratory research and when used in combination with other metrics, such as perceptual or physiological ones. However, using these same metrics, one can build a solid theoretical foundation related to attention and attention-related constructs. Some researchers have done so by using theories of visual attention to interpret eye-tracking metrics. Researchers need to more deeply explain the intricacies of the constructs of interest to create an operationalization that reflects the constructs at the conceptual level and, thus, better ensure content validity.

However, eye-tracking and attention must be considered within a specific context. Visual fixation could depend on the individual's familiarity (Cortinas et al., 2019) or could indicate both interest and difficulty in processing. Visual attention could also be unconscious and unrelated to individuals' preferences (Vraga et al., 2019). These examples further demonstrate that researchers should complement eye-tracking with qualitative information and control variables.

Additionally, attention differs from remembering information. Indeed, when people see visual information, they have to encode it through attention, store it through memory, and then retrieve it by reactivating the mental representation (Lang, 2000). Visual attention theories and the limited capacity model of mediated message processing constitute central tenets of using eye-tracking to measure attention (Vraga et al., 2019).

Once researchers have explored the theoretical ground, the next step is to increase the methodological complexity of analyses. Using scan-path information to link gaze with temporal data, pattern analyses can utilize machine learning technologies to show how gaze can switch between different AOIs.

However, researchers can also use eye-tracking analyses and reporting methods in other ways not seen in our sample. The top left quadrant in Figure 6 appears blank since research with low theoretical complexity and high methodological complexity does not exist in the IS field. We could see it as a sign that IS research relies heavily on deductive research. Indeed, the IS field has received criticism for lacking data-driven research (Grover & Lyytinen, 2015). IS outlets do not seem to publish research papers that lack a theoretical background. However, using eye-tracking to predict eye movement and processes could have some value. For example, other research fields have developed transitional matrices (Chuk et al., 2014; Sharafi et al., 2015) to identify the probability that individuals will switch from one area of interest to the next, or classified individuals based on their eye movement. Doing so requires a different methodology, such as using a large dataset with machine learning algorithms, but does not necessarily require a theoretical basis. Such research is more exploratory in nature and uses eye-tracking variables as independent variables. Researchers could take advantage of the evolving accessibility of eye-tracking technologies to gather larger datasets for clustering information and identifying new patterns that could inform future theories rather than relying on pre-existing theories.

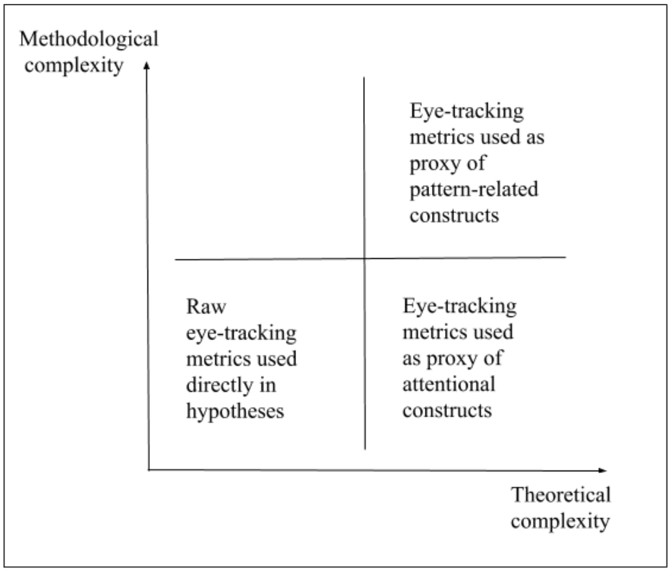

Figure 6. Methodological and Theoretical Complexity of Eye-tracking IS Research

4.2.4 Triangulation of Eye-tracking Data

An important challenge lies in understanding which constructs can be predicted by gaze behavior and fixation patterns. By investigating this issue more closely, researchers should be able to increase the list of constructs they can analyze with eye-tracking metrics.

Most research in our sample used a quantitative rather than a qualitative approach. However, we also need to pursue qualitative analyses to gain an understanding of higher-level constructs. It is possible to develop eye-tracking procedures to empirically explain theory-derived guidelines by exposing the underlying cognitive processes of behaviors. In conceptual modeling, researchers have used the scan path analysis to predict how quickly individuals learn (Bera & Poels, 2019; Bera et al., 2019). Researchers could explore other behaviors and contexts in the same way.

Research that has used gaze-behavior metrics as IVs shows that eye-tracking has great promise in predicting behavioral outcomes. However, since most research focused on eye-tracking metrics as DVs, these studies constitute only a small portion of the work in this area.

Few papers in our sample used eye-tracking in conjunction with other signals to collect data on when users focused on an AOI. Eye-tracking can be used in conjunction with other signals such as surveys, EEG, and other physiological measures (Courtemanche et al., 2018; Riedl & Léger, 2016). For example, few studies in our sample used pupil measurement despite its established relationship with sympathetic activation and cognitive load (Bradley et al., 2008). Researchers could benefit from integrating pupil measurement in their research to complement other measures of cognitive load and arousal. Indeed, most eye-tracking devices can measure these metrics in addition to gaze measurements without a need to change the apparatus or the settings. Lee et al. (2019) conducted eye-tracking research on the role that prior knowledge plays in problem-solving during IS-assisted medical training. They measured cognitive load using a questionnaire. A potential area for improvement would be to analyze pupil response. Adding the pupil measure could have highlighted the precise moment when cognitive load varied and could have provided insight to improve the design of the system. Additionally, pupil measures could provide information about how individuals react to specific system aspects rather than using an average value of cognitive load across the entire session.

One can perform triangulation with many types of data sources beyond physiological data. For example, Blascheck et al. (2017) developed a method that involves eye-tracking, interaction with a mouse, and think-aloud data that they synchronized and analyzed with both visualization and a string-based analysis. Their triangulation method allowed them to use eye-tracking data as a reference for what the task was about, while the mouse click showed how participants executed the task, and the think-aloud provided insight into why they did it (Blascheck et al., 2016). IS research typically uses experimental settings, questionnaires, surveys, and interviews to answer specific questions. Similarly, they should consider eye-tracking as a tool in their toolset rather than viewing eye-tracking as a specific and isolated asset.

5 Conclusion

In this review, we addressed the role that eye-tracking has played in the IS field. We examined the experimental settings and the type of analyses used in eye-tracking research in the IS field. We found that experimental settings, metrics, and analyses have evolved over time. However, there are opportunities and potential to address research questions better and in greater depth by taking advantage of available hardware and software options such as mobile tracking, visualizations, and more insightful methodological analysis techniques. Specifically, we recommend researchers use machine learning techniques to analyze more than just fixations and saccades but also the temporality and movement between different areas. We also recommend that IS researchers use quantitative and qualitative eye-tracking data in conjunction with other measurements to triangulate their findings. Finally, we recommend that researchers explore mobile eye-tracking since mobile Internet usage accounts for 67.81% of U.S. Internet traffic (Oberlo, 2023).

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Appendix A: Outlets Considered for the Search Phase

- ACM SIGMIS Database
- *ACM Transactions on Computer-Human Interaction*
- *ACM Transactions on Information Systems*
- *ACM Transactions on Management Information Systems*
- *AIS Transactions on Enterprise Systems*
- *AIS Transactions on Human-Computer Interaction*
- *Australasian Journal of Information Systems*
- *Business Information Systems Engineering*
- *Business Process Management Workshops*
- *Communications of the ACM*
- *Communications of the AIS*
- *Computer Supported Cooperative Work*
- *Computers in Human Behavior*
- *Decision Sciences*
- *Decision Support Systems*
- *Electronic Commerce Research*
- *Electronic Commerce Research and Applications*
- *Electronic Markets*
- *Enterprise Modelling and Information Systems Architectures*
- *European Journal of Information Systems*
- *Human-Computer Interaction*
- *IBM Journal of Research and Development*
- *IEEE Transactions on Systems Man, and Cybernetics*
- *Information and Management*
- *Information and Organization*
- *Information Systems*
- *Information Systems and e-Business Management*
- *Information Systems Frontiers*
- *Information Systems Journal*
- *Information Systems Management*
- *Information Systems Research*
- *Information Technology and Management*
- *Informing Science*
- *International Journal of Electronic Business*
- *International Journal of Electronic Commerce*
- *International Journal of Information Management*
- *International Journal of Information Technology & Decision Making*
- *International Journal of Knowledge Management*
- *International Journal of Mobile Communications*
- *Journal of Computer Information Systems*
- *Journal of Computer-Mediated Communication*
- *Journal of Decision Systems*

- *Journal of Electronic Commerce in Organizations*
- *Journal of Electronic Commerce Research*
- *Journal of Enterprise Information Management*
- *Journal of Information Systems*
- *Journal of Information Technology Theory and Application*
- *Journal of Information Technology*
- *Journal of Management Information Systems*
- *Journal of Organizational Computing and Electronic Commerce*
- *Journal of the ACM*
- *Journal of the AIS*
- *Lecture Notes in Business Information Processing*
- *Management Information Systems Quarterly Executive*
- *Management Information Systems Quarterly*
- *Proceedings of SIGHCI*
- *Proceedings of the Americas Conference on Information Systems*
- *Proceedings of the European Conference on Information Systems*
- *Proceedings of the Hawaii International Conference on System Sciences*
- *Proceedings of the International Conference on Advanced Information Systems Engineering*
- *Proceedings of the International Conference on Design Science Research in Information Systems and Technology*
- *Proceedings of the International Conference on Information Systems*
- *Proceedings of the Internationale Tagung Wirtschaftsinformatik*
- *Proceedings of the Midwest Association for Information Systems*
- *Proceedings of the Multikonferenz Wirtschaftsinformatik*
- *Proceedings of the Pacific Asia Conference on Information Systems*
- *Scandinavian Journal of Information Systems*
- *The Journal of Strategic Information Systems*

Appendix B: Outlets Represented in the Final Sample

Journals

- *ACM Transactions on Computer-Human Interaction*
- *ACM Transactions on Information Systems*
- *AIS Transactions on Human-Computer Interaction*
- *Communications of the ACM*
- *Computers in Human Behavior*
- *Decision Sciences*
- *Decision Support Systems*
- *Electronic Commerce Research*
- *Electronic Commerce Research and Applications*
- *Enterprise Information Systems*
- *European Journal of Information Systems*
- *Information & Management*
- *Information System Research*
- *Information Systems Frontier*
- *Information Systems Journal*
- *Information Systems Research*
- *International Journal of Electronic Commerce*
- *International Journal of Information Management*
- *Journal of Computer Information Systems*
- *Journal of Computer-Mediated Communication*
- *Journal of Management Information Systems*
- *Journal of organizational computing and electronic commerce*
- *Journal of the Association for Information Systems*
- *MIS Quarterly*

Conferences

- Americas Conference on Information Systems
- Enterprise, Business-Process and Information Systems Modeling
- EuroSymposium on Systems Analysis and Design
- International Conference on Advanced Information Systems Engineering
- International Conference on Business Process Management
- International Conference on Information Systems
- Lecture Notes in Business Information Processing
- Proceedings of the Annual Hawaii International Conference on System Sciences
- Wirtschaftsinformatik
- Wuhan International Conference on E-Business

Appendix C

Table C1. Papers in the Review

Papers		
Ahn et al. (2018)	Hamborg et al. (2012)	Ponce & Mayer (2014)
Amblee et al. (2017)	Hernández-Méndez & Muñoz-Leiva (2015)	Proudfoot et al. (2016)
Andaloussi et al. (2019)	Ho (2014)	Reani et al. (2014)
Anderson et al. (2016a)	Huang & Kuo (2012)	Ruf & Ploetzner (2014)
Anderson et al. (2016b)	Huang (2018)	Schneider et al. (2016).
Bahr & Ford (2011)	Jaeger & Eckhardt (2021)	Scott & Hand (2016)
Bailey & Iqbal (2008)	Jamet (2014)	Sheng & Joginapelly (2012)
Bang & Wojdynski (2016)	Jay et al. (2013)	Shojaeizadeh et al. (2017)
Bera & Poels (2019)	Jensen et al. (2016)	Shojaeizadeh et al. (2019)
Bera (2014)	Lee & Ahn (2012)	Steinfeld (2016)
Bera (2016)	Lee et al. (2015)	Steinfeld et al. (2016)
Bera et al. (2019)	Lee et al. (2019)	Still (2018)
Brasel & Gips (2017)	Leuthold et al. (2011)	Taub et al. (2017)
Castilla et al. (2016)	Li et al. (2016)	Tzafilkou & Protogeros (2017)
Chen et al. (2019)	Liginlal et al. (2016)	Vance et al. (2018)
Cole et al. (2015)	Lin et al. (2016)	Vraga et al. (2019)
Cortinas et al. (2019)	Linfeng et al. (2013)	Walhout et al. (2015)
Cyr et al. (2009)	Liu & Chuang (2011)	Wang & Hung (2019)
Djamasbi et al. (2010)	Liu et al. (2018)	Wang et al. (2014a)
Djamasbi et al. (2011)	Liu et al. (2017)	Wang et al. (2014b)
Djamasbi et al. (2012a)	Lo et al. (2014)	Wang et al. (2016a)
Djamasbi et al. (2012b)	Luan et al. (2016)	Wang et al. (2016b)
Djamasbi et al. (2012c)	Meppelink & Bol (2015)	Wang et al. (2017)
Djamasbi et al. (2014)	Meservy et al. (2014)	Wang et al. (2018)
Dogusoy-Taylan & Cagiltay (2014)	Mikalef et al. (2020)	Watrobski et al. (2017)
Dunaway et al. (2018)	Molina et al. (2014)	Weber et al. (2016).
Eckhardt et al. (2013)	Morana et al. (2017)	Willems et al. (2019)
Ellison et al. (2020)	Mou & Shin (2018)	Windels et al. (2018)
Etco et al. (2017)	Nadj et al. (2020)	Wong (2020)
Fadel et al. (2015)	Ozcelik et al. (2010)	Yang & Lin (2014)
Fehrenbacher & Djamasbi (2017)	Pak & Zhou (2013)	Yang (2014)
Fehrenbacher & Smith (2014)	Pantazos & Vatrapu (2016)	Ye et al. (2013)
Fehrenbacher & Tracy (2016)	Park et al. (2020)	Ye et al. (2020)
Fehrenbacher (2017)	Pengnate (2016)	Yen & Wu (2017)
Flavián-Blanco et al. (2011)	Perrin et al. (2014)	Zhou et al. (2015)
Fu et al. (2020)	Petrusel & Mendling (2013)	
Groen & Noyes (2010)	Petrusel et al. (2017)	
Groff et al. (2014)	Pinggera et al. (2013)	

Appendix D: Topics of Interest

This appendix reports how we coded the topics of interest. We developed our code scheme iteratively after reading each paper. In the end, we had four main categories: individual-, task-, device-, and design-related characteristics. Below we list all the topics in each category. Table 8 highlights the role that each element plays in eye-tracking outcomes. For example, under the individual characteristics, eye-tracking based IS research investigated the effect that mood or expertise had on eye-based metrics (such as attention or information-search pattern).

Table 8. Categories and Topics of Interest

Individual	Device	Task	Design
Behavior	Device type	Deceptiveness	Ad type
Elaboration level	Device orientation	External pressure	Aesthetics
Expertise		Task completion	Content type
Familiarity		Task complexity	Cues
Health literacy		Task load	Formatting of information
Motivation		Task type	Presence of human faces
Personal interest			Nature of information
Previous experience			Redundancy of information
Prior knowledge			Smile type
Purchase intention			Text content
Reasoning ability			Visual elements
User type			Visual presentation
			Website quality

About the Authors

Aurélie Vasseur is a Doctoral Student in Information Systems and a member of the Tech3Lab at HEC Montréal. Her research focuses on user experience and the neurophysiological responses to IS use. Her work has been presented at the International NeuroIS retreat, and she is a HICSS Doctoral Fellow.

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Pierre-Majorique Léger is a full professor at HEC Montréal and holds the NSERC-Prompt Industrial Research Chair in User Experience. He holds a PhD in Industrial Engineering from École Polytechnique de Montréal. His research aims to improve the UX experienced when using information technology, by mobilizing the biophysiological data generated during an interaction to qualify the user's emotion and cognition.