언론정보학과 석사학위논문

The Effects of Visual Elements on User's Attention and Information Recall for Contextually-Appropriate Visual News Generation

사용자의 컨텍스트를 고려한 시각적 뉴스 생성에서 시각 정보 요소가 사용자의 주의와 정보 회상에 미치는 영향

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Abstract

Automated news generation systems have been generating text-based news articles ever since the advancement of Natural Language Processing and machine-learning algorithms. Although automatic generation of text-based articles are effective in communicating information to users, the next step in the automated production of articles would be including visual elements such as images, tables, and infographics. However, the challenge of incorporating visual elements into automated news generation relies on translating the human designer's iterative design process into numerical values, which involves selecting pertinent set of visual elements according to the context in which the information will be displayed on. In order to automate this process, the visual elements must be scored to be weighed and selected according to context. One way to assign values on the visual elements in news articles is through determining the level of saliency on each element, since it reflects the hierarchy of information. Accordingly, this research measured the saliency of visual elements by observing its effect on user's visual attention and information recall. Also, this study chose 'attentional state' and 'information behavior' as two contexts in which the visual elements must be weighed against. The results indicate that each context provided a different range of saliency scores for visual attention and information recall. This suggested a possibility in using saliency

scores as a method to implement visual elements in automatic visual news generation.

Keywords: visual elements, visual attention, information recall, robot journalism, automatic news generation

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1. Introduction

Automatically generated news articles, otherwise known as 'automated journalism' or 'robot journalism', has recently been popularized due to the advancement of statistical methods and machine learning (Dörr, 2016). Automated journalism is an automated news production process that incorporates algorithm in aggregating data to final production of news (Van Dalen, 2012). Advances in Natural Language Generation and linguistics has propelled automated news generation systems to produce text that emulates writing styles by a human writer from computational representation of information (Clerwall, 2014). This made the aggregated data more digestible to read for regular news readers, making it commercially acceptable to be utilized in online news outlets such as the Associated Press[1], The Los Angeles Times[2], and The Washington Post[3].

The benefits of automated journalism are in its power to make automatic decisions in reporting real-time news and create variations of a specific issue in speed and cost that no human journalist can emulate (Diakopoulos, 2015; Van

[1] https://insights.ap.org/industry-trends/report-how-artificial-intelligence-will-impact-journalism

[2] http://www.latimes.com/local/lanow/la-me-earthquakesa-earthquake-42-quake-strikes-near-scissors-crossing-calif-cbr3-story.html

[3] https://www.washingtonpost.com/pr/wp/2016/08/05/the-washington-post-experiments-with-automated-storytelling-to-help-power-2016-rio-olympics-coverage/

Dalen, 2012). The most common type of automated news currently available is a text-based article that creates a narrative in a journalistic writing style (Figure 1).

SHOCKER VICTORY

English Premier League - 08/08/2015 - Traveling Watford and Everton split the points after 2-2 draw.

It was an even contest between Watford and Everton as the two played to a 2-2 draw. Watford took an early advantage, leading 1-0 heading into the break. However, Everton clawed their way back in the second half to earn a share of the points.

While evenly matched on the scoreboard, Watford outshot Everton 11-10, with both teams hitting the target five times. Everton finished the game with eight corner kicks, while Watford earned two.

Referee M Jones was not forced to be too involved as it was a relatively easy match to manage. Watford were responsible for the majority of the fouls, finishing with 13 fouls compared to only seven by Everton. Similarly, the visitors finished with two yellow cards, compared to the hosts' one.

Figure 1. Example of text-based automated article on a soccer sports recap. Generated by Wordsmith on Automated Insights

The automated news generation systems can present these text-based articles in various text lengths, adjusted to different kinds of screen-sizes and environments[4].

However, majority of automatic news generation systems are limited to publishing text-only news and needs to consider implementing visual elements to its system. The acceleration of information and public access to the Internet has shifted the presentation of news towards more "scannable artifacts" (Cooke, 2005). According to Cooke, it was found that news presentation designs were shifting to a more 'spacious modular layout' featuring visual elements (i.e.

[4] https://automatedinsights.com/wordsmith

information graphics, pictures) as the dominant form of communication as early as the mid-1970s. A study by Knox (2007) also indicated that as news stories become more 'atomized' and the readings of texts become more 'traversal', the structure in which news is visually-verbally positioned was becoming increasingly important. Furthermore, current news readers have a tendency to prefer succinct, image-oriented articles (Leckner, 2012). In response to this, modern news media platforms have been producing visual-centric news articles. For example, The Upshot Newsletter by The New York Times regularly post visual news stories and data visualizations[5]. Medium, Buzzfeed News, Vox.com, and many more online media platforms often utilize swipe-able cards with images to engage the readers and get information across. Therefore, it will be beneficial for the field of automated journalism to incorporate visual elements other than text – that is, images, tables, infographics, etc. – to its system.

The challenge of incorporating visual elements into automated news generation lies on automating the human designer's decision-making process of selecting appropriate visual elements for each news article. A human designer or an editor will always weigh what the most pertinent set of visual elements will be based on the context in which the information will be displayed on. In other words, the 'appropriateness' of each visual element will be decided upon where it needs to be displayed, what information needs to be emphasized, who the

[5] https://www.nytimes.com/interactive/2018/12/23/upshot/nfl-playoff-trees-week-17.html

audience is, what the goal of the audience is, etc. A human designer's design process consists of identifying these 'contexts', or 'constraints', and figuring out how to satisfy each of these constraints through a number of design iterations. During the iterative process, the designer will weigh each of these constraints and create several design alternatives with variations of visual elements and layout. The designer's decision for the most optimal set of visual elements and layout will be based on the alternative that satisfies all the constraints.

Automating the process of selecting appropriate visual elements require translating the designer's iterative process into numerical values to be weighed and scored as well. The numerical optimization process in simulated annealing methods use similar process to that of a human designer's iterative decision making (González, Rojas, Pomares, Salmerón, & Merelo, 2002). This process weighs the maximum and minimum values of a given function and outputs the most optimal value for a given set of constraints (Nocedal & Wright, 1999). For example, if the reader's contexts are the set of constraints to be satisfied when making the decisions on appropriate visual element selection, the values of each visual element will be weighed and scored based on these contexts. A visual element that scored a high value in one context might be weighed and scored very low in another situation. Thus, the most 'contextually-appropriate' set of visual elements on a page will always have the most optimal score out of all the iterations. However, current automated news generation process does not have an

empirical work on the values of visual elements according to these contexts. Therefore, in order to automate the process of selecting appropriate visual elements, visual elements presented in news articles need to be translated into values that can be weighed and scored.

One way to assign values on the visual elements in news articles is through determining the level of saliency on each element. In the case of designing news articles, the most optimal set of visual elements are decided upon how it reflects the information hierarchy of the article. News articles will always have a set of information that has a hierarchical order of importance. In order to select visual elements that reflect the information hierarchy, designers assign various degrees of salience onto the elements. "Saliency" has been defined as the degree of which individual elements in a visual field attract attention (Chun & Wolfe, 2001). Degrees of saliency creates a hierarchy of importance among elements on the page, guiding the reader from highest to the lowest salient element (Smith, Moriarty, Kenney, & Barbatsis, 2004). Thus, the saliency of visual elements guide reader's visual attention to relevant information that are worthy of immediate concentration than others (Kress & Van Leeuwen, 1998). Also, using degrees of saliency for perceptual organization and hierarchy has been known to expedite information processing, thus providing effective visual communication (Frascara, 2004; Smith et al., 2004). Saliency of any object or an element is often measured in terms of user's visual attention, through eye-tracking method (Bruce

& Tsotsos, 2009; Holmqvist & Wartenberg, 2005; Jacob & Karn, 2003). Therefore, this study examined the effects of visual elements in terms visual attention scores to determine the different levels of saliency. In addition, this study observed the information recall of each visual elements to find out if the hierarchical order of salient items on a news article were effective in user's information processing as well.

The reason for observing the effects of visual elements based on context is because the human designer's iterative process involve weighing each context in which the information will be displayed on. However, the automation process do not have human designers to weigh each visual element according to context. Not only that, the numerical optimization process—a similar automation method used in optimal display designs—also weigh the scores of each element per context to eventually obtain the most optimal layout. Therefore, this study considered contexts relevant to online news reading in order to observe if the visual elements display different effects on reader's visual attention and information processing. By observing the effect of visual elements based on different contexts, this study was able to establish a methodology that could be used in scoring and weighing other specific visual elements that can be used in automatic news generation process.

This study considered the interplaying situations of 'attentional state' and 'information behavior' as two contexts to observe the effects of visual elements.

This is because previous studies suggest these two concepts influence the visual attention and information processing when viewing and reading information (Rensink, 2011). These two contexts were also chosen because psychological contexts, such as the activity and state of the users, have been considerably understudied compared to physical contexts. Observing psychological contexts is also meaningful because advancement of technology have allowed us to determine the appropriate presentation of content by detecting user's attention and intention (Roda & Thomas, 2006). By observing the effects of visual elements based on psychological context of users, this study provided valuable insights for 'context-aware' systems in general.

In sum, the goal of this study was to provide a methodology in assigning scoring values for contextually-appropriate automatic visual news generation. In order to achieve this goal, seven articles with various forms of visual element and combination of visual elements were selected and created as stimuli. Then, a lab-experiment with four different experimental conditions were created to simulate reader's contexts when reading an online news article. An eye-tracking device was utilized to measure participants' visual attention of these stimuli. Post-test questionnaires on the content of the article observed the effects of visual elements on reader's information processing, measured through participants' information recall. The quantitative data collected were analyzed using general linear models to determine how each visual element and combination of visual elements affect

user's visual attention and information recall. This research ends with a discussion of the results and a conclusion on using this study as a general method of assigning scores for contextually-appropriate automatic visual news generation.

2. Literature Review

2.1. Automated Journalism

Academic papers on the topic of automated journalism over the few years seem to be focused more on the public perceptions and societal impact of the computer-written articles, migrating from the initial development and implementation part of the research (Allen et. al, 2010; Birnbaum et. al, 2013; Diakopoulos, 2011). This is due to the accumulation of real-world applications of automated news contents in online publications such as The Associated Press and Los Angeles Times. The following researches in response to this were divided into two directions— the public and journalists' perceptions of computer-generated news, and studying the ethical, cultural, and societal issues of automated journalism. In general, the public perceptions of automatically generated news examined its quality and value of news (Clerwall, 2014; Carlson, 2015; Haim & Graefe, 2017). The other body of research addresses the political, ethical, and economical implications that automation of news articles can bring to the society (Latar, 2015; Saurwein, Just, & Latzer, 2015; Diakopoulos & Koliska, 2017; Van Dalen, 2012). These topics however, such as transparency and credibility of computer-written news, will be limited in discussion since the focus of this study will be examining how to improve the communication of automated content through incorporating contextually-appropriate visual elements.

Another line of research in automatic news generation process is invested in improving the computational algorithm by incorporating different types of visual

elements (e.g. graphics and images) and other multimedia files (e.g. audio and video) which contribute to the presentation of the news article (Royal, 2010). One example of this attempt is a recent study by Ha et. al (2015). This study noticed that a compact representation is a key issue for effective information delivery, especially to readers who access news in mobile devices. With this in mind, they proposed a new algorithm that generated image-based contents from summarizing text-based news articles. The image-based contents had sentence embedded in the images to improve readability. However, the study by Ha et. al (2015) did not evaluate the actual readability of the news articles and only suggested the formal assessment in their future work. In other case, a research by Kim (2017) developed a new algorithmic framework in which the presentation of news information was considered. The news presentation utilized user interface elements and interactive format in order to generate personalized news stories in a timeline visualization. The timeline visualization was implemented to help users understand the overall flow of the news easier and faster. Kim (2017) examined the effects of his new algorithmic framework and verified that it improved the perceived news quality of the computer-generated articles. However, the visual elements that were chosen to be implemented onto automated systems were chosen manually by the researcher and no further investigation on the effect of visual elements were conducted.

To sum up, there is a lack of research within the field of automated

journalism to fully automate the process of selecting appropriate visual elements onto a news article. For those researches that investigated incorporating visual elements within automated generation systems, the visual elements were designated by the researchers and the effect of the elements on users were not evaluated. Therefore, this study aimed to examine how visual elements pertinent to news articles affected reader's visual and information processing in order to lay down a groundwork for choosing appropriate visual elements within automated news generation system.

2.2. Reader's Contexts

The effect of visual elements on a display depends on the situations, or context, by the user. Most current user interfaces, however, do not carefully consider these situations thereby displaying information that require same cognitive effort no matter what the current state of the user is. In Human-Computer Interaction studies, a 'context' is defined as "any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user" and "an application, including the user and applications themselves (Dey, 2001)". The information that can characterize the context of an entity typically includes the "location, identity, activity, and state of people, group and objects" when using a particular system (Salber, Dey, & Abowd, 1999). These physiological-

psychological contexts are often used as basis for developing information displays, in order to provide information at appropriate levels of granularity using organizational structures pertinent to users and their tasks (Marchionini, 1997).

The contexts that were used to observe the effects of visual elements in this study were the interacting situations of user's attentional state (focused vs. divided attention) and information behavior (browsing vs. searching). Both of these concepts affect readers' attention, thereby affecting how information is processed (Egeth & Yantis, 1997). The reason for constructing an interplay of these two contexts was to observe the effect of visual elements in conditions that were as close to real-world situations as possible. In other words, real world situations where users are reading an online news article involves a lot of noise. People may be entirely focused and searching for a specific information on an article, or they might be multi-tasking while casually browsing through an article. The interplay of these two contexts allow observations on reader's visual and information processing of the visual elements, thus providing a basis to construct news articles appropriate to various situations readers are in. Therefore, this study examined the interacting situations of attentional state and information behavior, and categorized the final four contexts as follows: *Focused Attention and Browsing, Focused Attention and Searching, Divided Attention and Browsing,* and *Divided Attention and Searching.* The following sections describe the concept of user's attentional state and information behavior in detail.

2.2.1. Attentional State

The advancement in information technologies in today's society provide an information-rich world, where the information can be accessed anywhere and everywhere. The proliferation of information means that there is a limit in the ability of humans to attend to the wealth of information (Simon, 1996). According to Kahneman (1973), humans can only attend to a limited amount of information because they have limited capacity of attention. In other words, attention is a scarce resource. Thus, there needs a way to allocate attention in the most efficient way possible to minimize the mental effort in processing the information (Simon, 1996). One way to achieve attentional efficiency is by designing systems appropriately by varying the degree of salience on the presented elements so that minimal effort is expended and maximum amount of information is gained (Kreitler & Kreitler, 1972; Rensink, 2011).

However, in order to observe the effect of saliency on attentional efficiency, display systems must consider user's attentional states. This is because the amount of effort expanded in processing information differs according to the amount of attentional resource allocated by the user. "Attentional state" refers to the different amount of attentional resource allocated on the tasks at hand, based on the Multiple Resource Theory (Wickens, 1991). Naturally, people can voluntarily allocate more resource into one task, thereby increasing the task's performance. If the attention resources are divided between two activities, it is

said to be limited in supply, leading to a deterioration of performance on the tasks (Gopher & Donchin, 1986). In other words, when an attentional resource is allocated fully on one task, it can be said that a user has a high, focused attention. On the other hand, when attentional resource is dispersed on multiple tasks, it can be said that a user has a low, divided attention. Being able to access news anywhere means that users will have situations where the focus of attention is not solely on reading the news article. For example, if a user is walking while reading news on their mobile phone, he or she will have to allocate part of their attention to their motor skills such as walking, sudden movement, incoming obstacles etc. Likewise, If a user is performing multiple tasks at the same time, the attention of that person will be divided because relatively few items can be attended at any given time (Rensink, 2011). Division in user's attention hinders the tasks at hand, thereby increasing mental effort in processing the information (Wickens, 2008). Therefore, if a proper guidance of attention was given by the system in these 'divided' or 'focused' state, users will be able to obtain relevant information without increasing the mental effort.

These researches indicate that in order to increase attentional efficiency to process information, the state of the user's attention needs to be considered. Thus, the different attentional states of the user will be a relevant context to observe the varying effects of visual elements on readers' visual and information processing.

2.2.2. Human Information Behavior

Human information behavior, described as "the totality of human behavior in relation to sources and channels of information, including both active and passive information seeking, and information use (Wilson, 2000)", is a particular form of activity that users carry out when they encounter information such as news articles. To put simply, information behavior encompasses not only the active seeking of information, but passive seeking which includes unintentional behaviors, such as serendipitous discovery (Case, 2012). People who are actively seeking usually have a specific information that they need to acquire. For those who passively seek information have no pressing need to engage in an active effort to gather information but is available to absorb the information (Bates, 2002). The passive seeking of information can also be explained by the "Everyday Life Information Seeking Behavior" model (Savolainen, 1995). Yadamsuren & Erdelez (2011)'s study observes online news reading behavior based on this framework. The study revealed that online news reading happens either on a habitual basis or incidental exposure, due to routine task of reading news at specific time every day or by browsing or monitoring the Internet. In the information seeking literature, this activity has also been called 'maintaining current awareness' and has used the terms 'monitoring' and 'browsing' interchangeably (Bates, 2002).

As the digitization of news articles become more common due to the fast speed Internet and information technologies, online reading behaviors have been reflecting the human information behavior. For example, Liu (2005) examined an 80.5% increase in browsing and scanning behaviors in a screen-based environment, as well as an increase in selective reading (77.9% increase) and keyword spotting (72.6 % increase). Likewise, according to a nationwide (United States) survey of modern news consumers in 2016[6], two major types of news reading behaviors were identified: “seeking out" (44%) and “while doing other things” (55%). These two types of behaviors were driven by user’s intentionality—searching for specific information or serendipitous news consumption. The relationship between browsing and serendipitous discovery can be explained by “the act of people finding valuable information in other contexts than that in mind when the search was started” (Boyce, Meadow, & Kraft, 1994). Online news reading behaviors, therefore, have an ‘active’ and ‘passive’ way of information seeking—by actively seeking for a targeted information, or passively browsing for serendipitous discovery.

Browsing and searching activities driven by user’s intentionality is an important context that must be considered in observing the effects of visual elements on news articles. First, Grossberg (1999) proposes the Adaptive

[6] http://www.journalism.org/2016/07/07/the-modern-news-consumer/

Resonance Theory to explain how user's intentionality guides his or her attention by selectively amplifying some features while suppressing others to focus attention on information that matches the user's expectations. In this framework, intentions reflect expectations of events by the user which should take place in order to satisfy behavioral goals (Roda & Thomas, 2006). According to this theory, since users' attention will be focused on their intentions and behavioral goals, considering user's behavior will potentially help select appropriate visual elements in the news article. Therefore, information behavior will be a relevant context to observe.

2.3. Visual Elements in News Articles

Studies that examine the role of visual forms and elements in newspaper articles have diverse ways of defining what an actual visual form or an element is within a news article. The scope of these individual factors can be headlines, main text, images, infographics, as well as typography, color, and size. A study that examined reading behaviors in readers of print and online newspaper media defines these factors as 'visual cues', which include not only what has been listed above but also the position of an article on the page, the use of paragraphs, and typographical elements. Specific online 'visual cues' included icons, animated elements, location, order of headlines, etc (Leckner, 2012). On the other hand, researches that investigated multimedia effects on online newspaper articles and

websites define factors other than text in terms of its modality, which is defined as "a construct referring to the type of channels (text, picture, audio, and video) that are present in a communication scenario" (Kalyanaraman & Sundar, 2008). Within the scope multimedia effects, it is also defined as a 'code', as a result of sensory and perceptual processing of a message (Kalyanaraman & Ivory, 2009; Penney, 1989).

'Visual cues' or 'modalities' that were defined by previous studies do not quite fit into the definition of what this study aims to examine. This is because the scope of the visual forms in the study does not include the position or location of individual factors, nor does it include multimedia channels such as audio or video. Instead, the visual forms in this study will be individual elements that visually represent an information or a set of information, designed by a professionally experienced visual designer. This means that factors like color, size, position, typography is all included in the visual form. This study separates the textual elements with visual elements similar to Knox (2007), a study that examined the visual-verbal relationship of the text and visuals within a newspaper page. A "textual element" will represent information in a traditional text format. A "visual element" will be a visual representation of one or a set of information designated by a designer. It is important to note that the visual elements examined in this study do not represent the entirety of visual elements that can appear in news articles. Instead, this study focused on how the visual

elements that were created by human designers could be measured and valued in order to be used in the automatic visual news generation process. Therefore, we limited the scope of the visual elements to three different types of visual representation, each with its unique visual attributes that the professional visual designer deemed appropriate.

The three different visual elements examined in this study were: *Image, Table*, and *Infographic*. The reason why these visual elements were chosen was because they are common visual formats used in news reports. This study defined *Image* as a form of picture that represented an idea or an information. *Table* was defined as a form that represented a set of information systematically displayed in rows and columns, organized in lines and bounding boxes. Finally, *Infographic* is a form of information graphic that is a representation of information in a graphic format.

2.3.1. Visual Attention and Saliency

The study of visual elements and its perceptual effects have been researched in broad range of fields, such as cognitive psychology, visual communications, data visualization, etc. (Smith et al., 2004; Chun & Wolfe, 2001; Gunther & Van Leeuwen, 1996; Duncan, 1984). Researches in cognitive psychology explain that a highly salient item will 'pop-out' and draw our attention, driven by bottom-up mechanism in the human visual attention processing (Treisman, 1998). The visual

attention processing depends greatly on the perceptual saliency of an incoming stimuli, occurring involuntarily during the pre-attentive stage (Broadbent, 2013). On the other hand, the visual attention process also includes a top-down mechanism, which are largely driven by state and goals of the perceiver (Yantis, 1998). Top-down mechanisms are explained by cognitive process of the human brain, which determines whether one will be able to ignore incoming visual stimuli and focus on the object that one is consciously looking for in the visual field (Chun & Wolfe, 2001).

Generally, 'saliency' in information presentation is used to describe the process of assigning different degrees of visual cues (e.g. color, brightness, shape) and perceptual organization by the Gestalt principles (e.g. relative size, position) to attract the reader's attention. The different degrees of saliency creates a hierarchy of importance among elements, which directs attention to specific element over others (Kress & Van Leeuwen, 1998). Drawing selective attention through degree of salience is especially important in the domain of information presentation systems because it helps readers gasp maximum amount of information through a relatively minimum amount of effort (Kreitler & Kreitler, 1972; Casner, 1991), thus communicating information faster and with ease.

The domain of news information presentation has also extensively studied the saliency of visual elements that attract attention to the reader. However, the results do not point to a definitive solution (Leckner, 2012). Studies in this field

of newspaper design and screen media have acknowledged that a well-laid out presentation increases people's willingness to read and decreases the effort in reading (Wright, 1999; Smith et al., 2004). In response, researches have been utilizing eye-tracking methods to explore the principle cues and entry points that attract early attention on a newspaper or online page, which guides the reader in reading specific content (Holmqvist & Wartenberg, 2005; Bucher & Schumacher, 2006; Adam, Quinn, & Edmonds, 2007). However, due to reading behavior being a complex phenomenon and the instability of eye-tracking methods, the results were mixed in terms of which attributes of visual elements attract the most attention and to what degree (Garcia, Stark, & Miller, 1991; Leckner, 2012). Leckner (2012) asserts this is because reading behavior is affected by implicit and explicit factors, such as user goals and physical environments.

Another reason why visual attention studies on newspaper elements are inconsistent is because the measurement for observing 'visual attention' and thus, the saliency of visual elements, have been operationalized in various ways. The main measurements used in eye-tracking researches are *fixations*, which is 'a type of eye movement defined as a period of time during which the eye is relatively stable' (Hvelplund, 2014). Researches that utilize the eye-tracker to measure visual attention typically collect three metrics: *Time to First Fixation, Total Fixation Duration,* and *Number of Fixations.* These metrics are measured based on the "Area of Interest" that the researcher defines on the page. However,

fixations can be interpreted in various ways depending on context. For example, longer fixations can mean a greater saliency and interest in a browsing context; however, it can also mean longer processing of interpretation in a searching context (Jacob & Karn, 2003; Just & Carpenter, 1976). Also, the size of an area of interest greatly affects the overall eye fixation as well, as many researches note that size is an important factor in early fixations and saliency (Garcia, Stark, & Miller, 1991; Holmberg, 2004; Holmqvist & Wartenberg, 2005).

In response to the discrepancies of eye-tracking results, Rossi et al. (2017) proposed an 'Index of Visual Attention' which measures the 'visual engagement' produced by a visual stimuli. This studied utilized the eye-tracking measures to calculate a 'Visual Attention' score that reflects the saliency of different visual elements within health-promoting messages. The calculation controlled for the different size of elements that could potentially affect the visual attention. Also, it measured saliency as an overall visual engagement, which not only measures the reactions towards visual stimuli but how much visual information was processed and stored in our memory. This measurement is more in line with the objective of this research, which was to measure the visual attention of elements within a news article to observe how it influenced the visual and information processing of readers. Therefore, we define the saliency measured through visual attention as an overall visual engagement that an element imposed upon the reader.

2.3.2. Information Recall

Scholarly research in the field of journalism and news media have long been studying the use of graphics and visuals and its effects on information recall, with contrasting results. For example, Peterson (1983) have found the use of tables, graphs, and maps enhance reader performance and recall. Likewise, the Poynter Institute study on design factors and recall of newspaper revealed that 'graphics-laden' presentation had the best information recall (García, Stark, Miller, & Studies, 1991). The higher recall of visual elements over textual information have been speculated to be the result of it being more salient, especially in the early stages of perception and thus drawing more attention (Harris & Jenkin, 2001). The higher saliency of visuals causes an 'amplifying effect', implying that it gets processed more efficiently and effectively into memory, and remembered better than texts. On the other hand, studies on multimedia effects have indicated that once more than one media was added to a news article, the recall decreased (Pipps, Walter, Endres, & Tabatcher, 2009; Tran, 2015). Also, the study by Sundar (2000) have found a negative impact of multimedia enhancements on processing of story content and perceptions of news websites. Melin (1999) have also noted that adding image with text contributed to a positive reception of the text, but decreased the memory retention of it. This was speculated to be because when image is integrated with text, it is more

cognitively demanding for the readers and increase the processing time in reading the article.

To sum up, researches on the recall of information has been a major variable of observation in information presentation and newspaper design studies because it is fundamental to information processing (Wells, Fuerst, & Palmer, 2005). However, previous researches in different fields of presentation studies indicate a contrasting result. This is perhaps because the visual elements that many of these studies were observing were in a wide range of variations. Or, other external factors such as prior knowledge, interest, education levels, etc. could have influenced the results (Lee & Kim, 2016). Although a consensus on the result of information recall is yet to be proposed, it is undeniable that it is an important measure in assessing visual presentations.

3. Research Question

Literature review within automated journalism and information design studies indicated that implementing visual elements within automatic news generation process require more attention and exploration for the following reasons. First, although past researches have attempted to include a variety of visual elements within an automated system, the elements were manually selected by the researchers or designers who knew what was befitting to each situation. Second, information design studies have shown that editors and designers engage in a high-level decision-making process that current automatic news presentation systems cannot follow. The designer's iterative process require experience in graphic and editorial design, and most importantly, the awareness of the context in which the news article will be presented in. In order to simulate the designer's process, there needs to be an empirical work that can provide a method in assigning proper values to visual elements that are to be used in automatic visual news generation. The values, or scores, also need to be observed based on context to simulate the designer's iterative process.

Previous studies on visual communication, information presentation, and cognitive psychology indicated that the saliency of visual elements can be a defining criterion of selecting appropriate elements for automated news generation system (Adam, Quinn, & Edmonds, 2007; Garcia et al., 1991; Holmqvist & Wartenberg, 2005; Rossi et al., 2017). Saliency of visual elements

draw visual attention by directing human eyes to highly salient items and eventually to items with lower salience, thus creating an order of elements that people attend to. In the field of information design, advertising, data visualization and more, saliency has been used to attract user's visual attention to specific element over the other, thus constructing a hierarchy of importance among the presented information (Kress & Van Leeuwen, 1998). Drawing selective attention through different levels of salience has been proven effective in the domain of information presentation systems because it helps users grasp information efficiently (Krietler & Krietler, 1972; Casner, 1991). Not only that, researches in newspaper design have examined how visual elements and its saliency can affect readers' recall and understanding of information. For example, studies have shown that including visual elements such as tables and infographics have increased information recall (Garcia, 2005; Peterson, 1983). However, some suggest including only one visual format within the newspaper for an increase in recall (Pipps et al., 2009; Sundar, 2000; Tran, 2015).

While these studies provide insightful findings about saliency of visual elements and its effects on visual attention and information processing, several limitations exist in terms of automating the decision-making process of appropriate visual selection. As mentioned above, deciding on what visual elements to include within a news article requires an awareness of the context in which the article will be presented in, since it affects the communication of those

elements. Literature review on user's contexts includes physiological contexts such as the location and identity of people, but psychological contexts as well—the state and activity of people (Salber, Dey, & Abowd, 1999). Previous studies and current practices in webpage design and information designs have long considered choosing appropriate visuals and format for different demographics and physical dimensions such as the form and location of display (data visualization article, etc.). In comparison, psychological contexts such as state and activity of people have been relatively understudied, since recognizing psychological state of users was difficult for systems. However, due to recent technological advancement in 'context-aware' systems, real-time data rendering, and automated news generation systems, exploring the effects of elements while considering the psychological context of users will provide valuable insights in choosing appropriate visual elements. Accordingly, this study focused on examining the effects of saliency of visual elements within user's psychological contexts. Specifically, this study chose 'attentional state' and 'information behavior' as user's contexts because previous studies have suggested these two factors influence the visual attention and information processing when viewing and reading information (Rensink, 2011; Wilson, 2000) . Thus, this study posits the following research questions:

RQ1) How does the visual elements in news articles influence user's visual attention based on reader's contexts?

RQ2) How does the visual elements in news articles influence user's information recall based on reader's contexts?

In sum, this research aimed to assess the effects of visual elements within different user contexts in order to examine a method that can effectively assign values to the visual elements, thus automating the decision-making process of visual news generation.

4. Research Method

The goal of this research was to examine the effects of visual elements within different psychological contexts (attentional state and information behavior) in order to provide an empirical method for automating the decision-making process of choosing appropriate visual elements. The contexts were an interaction of attentional state and information behavior, which created four conditions to observe the effects of visual element in. The four contexts were: *Focused Attention and Browsing, Focused Attention and Searching, Divided Attention and Browsing,* and *Divided Attention and Searching.* These four contexts were selected from previous studies indicating that 'attentional state' and 'information behavior' were major factors influencing the visual attention and information processing of readers (§2.2.). The reason why the contexts are an interplay of 'attentional state' and 'information behavior' was to set up experimental conditions that were as close to real-world situations as possible. Table 1 illustrates the four contexts in detail. The variables to be measured were users' visual attention and information recall of news articles with varying combinations of visual elements and text. To achieve the research objective, two expert designers with professional experience in information architecture and graphic design created the observable variation of visual elements within the news articles.

Table 1.
Description of each of the four conditions and real world example of the four contexts

		Information Behavior	
		Browsing Passive seeking of information without a particular intention (Savolainen, 1995)	*Searching* Active seeking of specific information (Bates, 2002)
Attentional State	*Focused Attention* Full allocation of attention on a single task (Wickens, 2008)	Ex. Reading a baseball recap article for an overall gist of the game	Ex. Searching for the MVP's name And his major play of the night from a sports recap article
	Divided Attention Partial allocation of attention on multiple tasks (Wickens, 2008)	Ex. Casually skimming through a news article while talking on the phone with a friend	Ex. Searching for a specific sports match results on a PC screen while walking to a bus station

Prior to the actual experiment, a pilot test was performed to assess the visual elements, news article content and design, and post-test questionnaires measuring recall. For the actual experiment, an eye-tracking system was used to measure participants' visual attention. A post-test questionnaire after each news article was conducted to measure participants' information recall. The following details characterized the design of experimental stimuli and experiment.

4.1. Participants

A total of 50 participants were recruited from mozip.snu.ac.kr, an online recruiting website. All participants were of Korean nationality. To qualify as a participant, he or she must have had healthy vision and knew how to operate a laptop computer. Two participants were excluded from the analysis because the eye-tracking device failed to record and measure the data. The average age of the final 48 participants was 26 years old (SD = 4.36) with similar distribution of both genders (45.8% female and 54.2% male). Most participants were students attending college. The average time the participants spent reading the online news was between 16~30 minutes per day. A total of 12 participants were randomly assigned to one of the four contexts.

4.2. Stimuli

The experimental stimuli used in the study were based on a comprehensive report of the overall weather of the day. Weather report is a suitable topic to be a case example for this research because the information presented is fairly straightforward. This makes the visual representation of information easier to interpret and assess as well. The process of choosing specific visual elements and its designs involved a meticulous amount of feedback from an experienced information designer and a visual designer a professional experience in visual design. After careful consideration of the types of visual elements to use in a

weather news article, three designs were chosen and defined for the experiment: *Image, Table,* and *Infographic*. The reason for the decision of these visual elements as stimuli is as follows. First, all three elements carry varying degrees of saliency due to its innate form. For example, *Table* is consisted of text and numbers in a tabular format, bound by a gray box. *Image* is a colored photograph of relevant information presented. *Infographic* is a combination of graphic symbols, colors, and shapes representing a particular weather data. Second, the goal of the study was to examine the possibility of making saliency as a scoring value for automatic visual news generation process. Therefore, we only needed a few representation of visual forms to examine the possibility through the experiment. By focusing on three specific visual elements, the experiment could concentrate on how each visual element affected user's attention and information recall according to different user contexts. Also, these three visual elements are commonly used in actual weather reports with just varying degrees of visual attributes. Thus, although we are observing three specific forms, it is still generalizable across other automated news topics, such as sports articles, stock reports, and presidential election summaries.

Total of seven different news articles containing different types of visual elements and combination of those elements were created. The articles were: 1) *Text only* (control), 2) *Text and Table*, 3) *Text and Image*, 4) *Text and Infographic*, 5) *Text, Table, and Image*, 6) *Text, Table, and Infographic,* 7) *Text,*

Image, and Infographic. Examples of the stimuli are shown in Figure 2. All seven of the news articles are presented in Appendix A.

This study have excluded the combination of all three visual elements (table, image, and infographic) within a news article for two reasons. First, the news articles needed to be controlled in the format, size, and dimensions. When including a third visual element, the article had to evidently 'scroll' within the computer display. Second, previous researches on different visual elements within newspaper design suggested that adding a third modality, whether it be

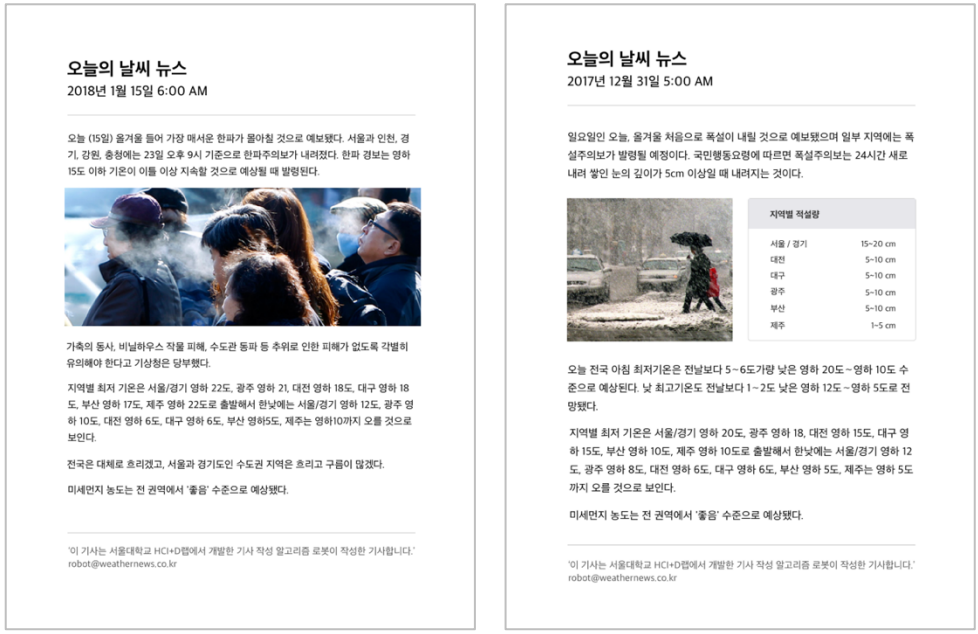


Figure 2. Examples of visual news articles shown to participants. *Text + Image* article on the left, *Text + Image + Table* article on the right. For the complete set of articles, refer to Appendix A.

infographics, audio, or video (Pipps et al., 2009; Sundar, 2000; Tran, 2015), decreased the recall and comprehension of the news article. Therefore, the combination of three elements were removed from examination.

All seven of the articles contained information about the national weather of the day in Korea, although the content varied in different significant events. For example, the “Text and Table” article emphasized on heavy rain with warning reports on the downpour, while “Text and Image” emphasized on below zero degree weather with a cold wave watch. The length, size, color of text, and the position of the date and title were controlled to keep consistency. The dimension of the articles was 768 x 1024px and shown on a 17 inch monitor display.

4.3.Apparatus

The eye-tracking system used for the experiment was Tobii X2-30 Compact device. The Tobii Pro Studio software was used to manage and record each participants data. A fixation was defined as a gaze of at least 100 milliseconds in the radius of 35 pixels. 100 milliseconds were chosen from previous eye-movement researches that established .10 seconds as the minimum amount of time necessary to be considered as a fixation (Baron, 1980; Fischer et al, 1989; Stark, 1994).

Eye tracking data were analyzed through Tobii Studio software for the extraction of information about fixations in each area of interest (AOI). The area of interest were each of the visual elements, defined by the researcher. Data such as the total fixation durations on each AOI, time to first fixations, number of

fixations, order of fixations were recorded.

4.4.Measures

4.4.1. Visual Attention

The effect of visual elements on reader's visual attention was measured by data gathered through the eye-tracker. In order to calculate the visual attention given to each visual elements, two measurements were extracted from the eye tracking data: total fixation duration on each Area of Interest (i.e. *Table , Image, Infographic)* and the area of each AOI. Then, the visual attention of elements was calculated using Rossi et. al (2017)'s index of Visual Attention:

$$VA = \%TFD / \%AREA$$

This index measured visual attention (VA) by calculating percentage of Total Fixation Duration on an AOI weighted on the total time the article was shown on the screen (%TFD), by the area of the AOI weighted on the total dimension of the stimuli (%AREA). The calculation controls for the impact of size on visual attention. Size, as studied in previous researches, have been a defining factor in early attention (Adam, Quinn, & Edmonds, 2007; Garcia, Stark, & Miller, 1991; Holmqvist & Wartenberg, 2005) in both print and online newspapers. However, since the focus of the study was observing the influence of visual elements and not the attributes of those elements, size needed to be controlled. In sum, the

calculation predicts that AOI reporting higher Visual Attention values will be the ones having more saliency.

4.4.2. Information Recall

The effect of visual elements on reader's information processing was measured in terms of information recall. Recall tests index how much information was stored and is available for retrieval (Sundar, 2000). The recall questionnaires were specifically designed to ask questions about the presented content of the article. For example, if the visual element of the first news article included the information of Seoul's sky condition, a recall question will ask the participant to select what the sky condition of Seoul was in a multiple choice questionnaire. There were a total of four recall questions per news article and were pilot tested on ten people and modified to achieve similar difficulty level. The full set of questions are presented in Appendix B.

4.5. Procedure

The experiment took place in a laboratory at Seoul National University. When the participants entered the lab, they were instructed sit in front of a laptop computer with the eye-tracking device set up in the middle of the room. After a brief introduction of the experiment and signing of the consent form, the participants filled out a pre-test questionnaire about their demographics and

frequency of reading online news. Before starting the experiment, an eye-tracking calibration was performed to measure individual's eye movements as accurately as possible.

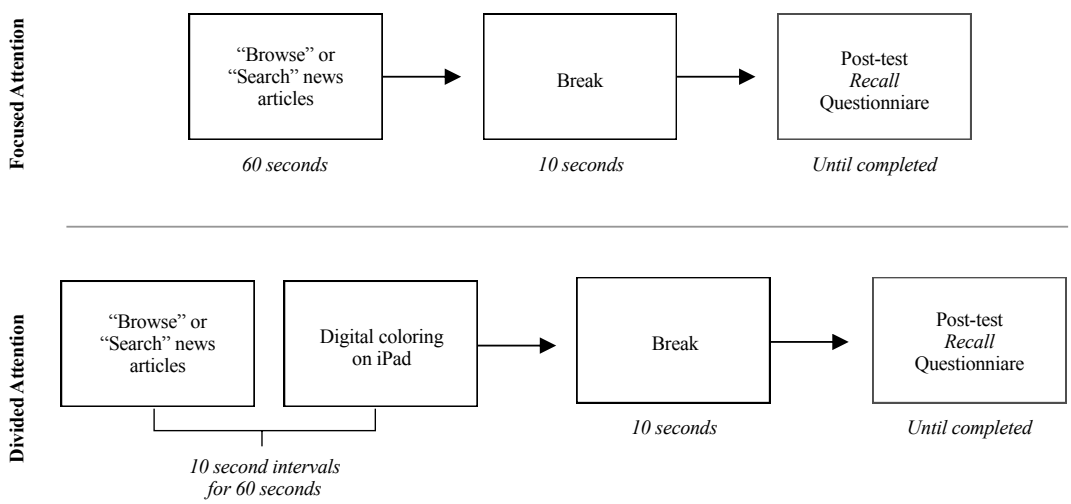
Participants in all contexts were instructed to read the news article that were going to be presented on the screen. All news articles were presented in random order for 60 seconds each on a laptop screen, with a distance from the subject varying from 50 ~ 60 cm. Between each stimuli, a blank screen with a "Please take a 10 second break" instruction was shown to establish a controlled time to respond to the information recall questionnaires after each stimuli. After the participants completed information recall questions for each article, they were instructed to press the spacebar of the computer to move on to the next stimuli. There were total of seven news articles shown, and the overall experiment took 30-40 minutes to complete. The participants were given 10,000 Korean Won as a compensation.

The participants were randomly assigned to one of the four conditions, each representing users' psychological contexts: A) *Focused attention & Browsing*, B) *Focused attention & Searching*, C) *Divided attention & Browsing*, D) *Divided attention & Searching*. Table 2 summarizes the four contexts, and the primary and secondary tasks that participants were instructed to perform. Details of the procedure is illustrated in Figure 3.

Table 2.
Summary of the tasks for the four contexts

		Information Behavior	
		Browsing	*Searching*
Attentional State	*Focused Attention*	**Primary Task:** Read news article on the monitor **Secondary Task:** N/A	**Primary Task:** Search for specific information in the news article **Secondary Task:** N/A
	Divided Attention	**Primary Task:** Freely browse the news article **Secondary Task:** Digital coloring on the iPad	**Primary Task:** Search for specific information in the news article **Secondary Task:** Digital coloring on the iPad

Figure 3.
Overview of the procedure



Participants in 'divided attentional state', or groups C and D, were given an iPad to complete a digital coloring task while reading the news articles. A timer

was placed next to the participant in order to control for the amount of time reading the article and the coloring task. The timer beeped in 10 second intervals, prompting the participant to go back and forth between the primary and secondary task. This dual-task method was chosen after pilot testing with several different online games on a desktop monitor. The problem with assigning a task such as an online game similar to Dabbish & Kraut (2004)'s research was that the eye-tracking device couldn't successfully record eye movements that deviated too far away from the device. Also, online games that required a secondary keyboard created too much movement and confusion within a 60 second frame and pilot participants failed to read the whole article. However, using an iPad that was placed fairly close to the eye-tracking device with a simple task of using one's finger to color in shapes allocated an apt amount of attention to the coloring task as well as the primary task, which was reading the news article. As for the conditions with 'focused attentional state' (groups A and B), the instructions were simply to read the news article when prompted.

For 'searching' conditions (groups B and D), the participants were instructed to search for particular weather information before each articles were presented to them. Each article had different information to be searched for. The conditions with 'browsing' behavior (groups A and C) were asked to freely browse the information in the presented article.

5. Results

For investigating the influence of visual elements on user's visual attention and information recall, general linear models were constructed for each element. General linear model was used to test several independent univariate tests to see if each of the visual elements as well as the combination of elements had any effect on visual attention and information recall. The results are organized by the four contexts observed in the experiment. Below is a concise description of the results, followed by detailed account of the results.

<u>Focused Attention and Browsing</u>

1) *Visual Attention: Image* in the article predicted a lower visual attention score than text in all articles including combination of visual elements (*Image & Infographic, Image & Table*). *Table* predicted a higher visual attention score than text in all articles including combination of visual elements (*Image & Table, Table & Infographic*). No significant effects were found for *Infographic.* Significant order of visual attention for *Image & Table* was *Table, Text,* and *Image*, respectively. Significant order of visual attention for *Table & Infographic* was *Table, Infographic,* and *Text*. Non-significant trend showed a predicted order of *Text, Infographic,* and *Image* for *Image & Infographic* article.

2) *Information Recall:* There were no significant effects across all visual elements for this context.

Focused Attention and Searching

1) *Visual Attention:* The results for this context was very similar to Focused Attention and Browsing. *Image* in the article predicted a lower visual attention score than text in all articles including combination of visual elements (*Image & Infographic, Image & Table*). *Table* predicted a higher visual attention score than text in all articles including combination of visual elements (*Image & Table, Table & Infographic*). No significant effects were found for *Infographic.* Significant order of visual attention for *Image & Table* was *Table, Text,* and *Image*, respectively. Significant order of visual attention for *Table & Infographic* was *Table, Infographic,* and *Text*. Non-significant trend showed a predicted order of *Text, Infographic,* and *Image* for *Image & Infographic* article.
2) *Information Recall:* No significant effects were found for *Image* and *Table*. However, *Infographic* in the article predicted a lower recall score than text. The combination of *Image & Infographic* in the article predicted a lower recall score as well. However, *Image & Table* in the article predicted a higher recall score than text. No significant effects were found

for *Table & Infographic*.

Divided Attention and Browsing

1) *Visual Attention:* The results of visual attention scores for this context varied the most among all contexts. *Image* in the article predicted a lower visual attention score than text in all articles including combination of visual elements (*Image & Infographic, Image & Table*). No significant effects were found for *Table & Infographic*. Significant order of visual attention for *Image & Table* was *Text, Table,* and *Image*, different from the rest of the context. Significant order of visual attention for *Table & Infographic* was *Infographic, Table,* and *Text*, although the difference between *Infographic* and *Table* were miniscule. Non-significant trend showed a predicted order of *Text, Infographic,* and *Image* for *Image & Infographic*.
2) *Information Recall:* Only one significant effect was found for this context: *Infographic*. *Infographic* in the article predicted a lower recall score than text.

Divided Attention and Searching

1) *Visual Attention: Image* in the article predicted a lower visual attention score than text in all articles including combination of visual elements (*Image &*

Infographic, Image & Table). *Table* predicted a higher visual attention score than text in all articles including combination of visual elements (*Image & Table, Table & Infographic*). No significant effects were found for *Infographic.* Significant order of visual attention for *Image & Table* was *Table, Text,* and *Image,* although the result for *Table* was marginal. Significant order of visual attention for *Table & Infographic* was *Infographic, Table,* and *Text*. Non-significant trend showed a predicted order of *Text, Infographic,* and *Image* for *Image & Infographic.*

2) *Information Recall:* No significant effects were found for *Image* and *Infographic*. However, *Table* in the article predicted a higher recall score than text. The combination of *Image & Infographic* in the article predicted a lower recall score. However, *Image & Table* in the article predicted a higher recall score than text. No significant effects were found for *Table & Infographic*.

5.1 Focused Attention and Browsing

5.1.1 Visual Attention

Descriptive statistics for the visual elements and its effects on Visual Attention are shown in Table 3 for the context of 'Focused Attention and Browsing'. The visual elements include *Image, Table,* and *Infographic.*

Table 3.
Descriptive statistics on the result of visual attention for Focused and Browsing context

	Variable	*M*	*SD*	*Min*	*Max*
Focused Attention and Browsing	Text(control)	0.548	0.646	0.003	2.035
	Image	0.348	0.373	0.006	1.406
	Table	1.143	0.811	0.054	3.166
	Infographic	0.744	0.657	0.010	2.395

The following Table 4 shows significant effects of *Image* and *Table* for having one element with the news article. Table 5 shows significant effect of *Image & Infographic*, *Image & Table*, and *Table & Infographic* for including two elements within the news article. The general linear model for *Infographic* had no significant effects.

Table 4.
General linear models for one element in a news article: Focused and Browsing

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	.881	.082	10.75	.000 ***	
Image	-.532	.143	-3.732	.000 ***	.132
(Intercept)	.537	.078	6.904	.000 ***	
Table	.606	.148	4.093	.000 ***	.154
(Intercept)	0.689	0.086	8.02	000 ***	
Infographic	.055	.1573	.351	.726	.001

*p <.05, ** p < .01, *** p < .001

Table 5.
General linear models for two elements in a news article: Focused and Browsing
*p <.05, ** p < .01, *** p < .001

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
ImagexInfographic	(Intercept)	0.99	0.109	9.067	.000 ***	0.153
	Image	-0.642	0.159	-4.029	.000 ***	
	Infographic	-0.246	0.164	-1.504	0.136	
	ImagexInfographic	NA	NA	NA	NA	
Image x Table	(Intercept)	0.696	0.103	6.744	.000 ***	0.200
	Image	-0.348	0.153	-2.276	0.023 *	
	Table	0.447	0.161	2.784	0.007 **	
	ImagexTable	NA	NA	NA	NA	
TablexInfographic	(Intercept)	0.393	0.099	3.958	.000 ***	0.199
	Table	0.750	0.158	4.743	.000 ***	
	Infographic	0.351	0.155	2.267	0.023 *	
	TablexInfographic	NA	NA	NA	NA	

Results for one visual element in a news article demonstrated that there was a significant effect for *Image* (β= -.523, F[1, 92]= 13.93, p = .000), than no *Image* in the article, indicating that image in the article predicts a lower visual attention score than text. Lower visual attention score, in terms of Index of Visual Attention (reference) refers to lower saliency in the element. Also, a statistical significance was shown for *Table* (β= .606, F[1, 92] = 16.75, p = .000) than no *Table* in the article, indicating that including a table predicts a higher visual attention score than just text.

As for the results of two visual elements in a news article, all three combinations showed significant effects, but no interacting effects between the visual elements. This analysis shows a reasonable result since it is not plausible to

have two visual elements interacting with each other to draw higher attention to both elements. Also, relevant eye-tracking research by Garcia and Stark (199) demonstrate that text and pictorial information tend to be processed at different times which results in a failure of significant interaction between two elements. That said, the article with *Image & Infograph*ic showed significant effects for *Image* only (β= -.642 F[2, 91] = 8.19, p = .000), illustrating that image within an article with both image and an infographic predicted a lower visual attention score. Also, a non-significant trending in the predicted direction indicated a higher visual attention score for *Infographic* than *Image*; however, text-only article had a higher score than both. The article with *Image & Table* demonstrated a significant effect for both *Image* (β= -.348, F[2, 91] = 11.35, p = .025) and *Table* (β= .447, F[2, 91] = 11.35, p = .007), indicating that an image in an article with both image and table predicted a lower visual attention score, whereas a table predicted a higher visual attention score. This suggests a significant trending in the predicted direction of having table draw greater attention than text, and eventually to the image. Finally, *Table & Infographic* showed a statistically significant effect for both *Table* (β= .750, F[2, 91] = 11.32, p = .000) and *Infographic* (β= .351, , F[2, 91] = 11.32, p = .023), showing that a table in an article with both table and infographic predicted a higher visual attention score, as well as an infographic. This indicates that table and infographic have higher

saliency than text, signifying a predicted direction of having table draw attention first, than to infographic, and finally to text.

5.1.2. Information Recall

Descriptive statistics for the visual elements and its effects on Information Recall are shown in Table 6 for the context of 'Focused Attention and Browsing'.

Table 6.
Descriptive Statistics on information recall for 'Focused and Browsing'

	Variable	*M*	*SD*	*Min*	*Max*
Focused Attention and Browsing	Image	3.17	0.58	2.00	4.00
	Table	3.33	0.78	2.00	4.00
	Infographic	2.75	0.97	1.00	4.00
	TablexInfographic	2.58	0.67	2.00	4.00
	ImagexInfographic	2.50	1.00	1.00	4.00
	ImagexTable	3.00	0.95	2.00	4.00

In order to observe the influence of visual elements on information recall, general linear models were constructed for each *Image, Table,* and *Infographic* as well as the combination of elements: *Table & Infographic, Image & Infographic*, and *Image & Table*. However, there were no significant effects on recall for any of the visual elements for the context 'Focused Attention and Browsing'. Appendix C includes the tables of the non-significant models for reference.

5.2. Focused Attention and Searching

5.2.2. Visual Attention

Descriptive statistics for the visual elements and its effects on visual attention are shown in Table 7 for the context of 'Focused Attention and Searching'.

Table 7.
Descriptive Statistics on visual attention for 'Focused and Searching'

	Variable	*M*	*SD*	*Min*	*Max*
Focused Attention and Searching	Text (control)	0.534	0.363	0.102	2.035
	Image	0.250	0.208	0.013	1.406
	Table	1.060	0.821	0.041	3.166
	Infographic	0.703	0.661	0.032	2.395

The following Table 8 shows significant effects of *Image* and *Table* for having one element with the news article. Table 9 shows significant effects of *Image & Infographic*, *Image & Table*, and *Table & Infographic* for including two elements within the news article. The general linear model for *Infographic* had no significant effects. Overall, the results were very similar to the context of 'Focused Attention and Browsing'.

Table 8.
General linear models for one element in a news article: Focused and Searching

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	0.823	0.071	11.59	.000 ***	
Image	-0.574	0.130	-4.415	.000 ***	0.1566
(Intercept)	0.486	0.071	6.867	.000 ***	
Table	0.574	0.131	4.372	.000 ***	0.154
(Intercept)	0.630	0.077	0.077	.000***	
Infographic	0.073	0.141	0.516	0.607	0.003

*p <.05, ** p < .01, *** p < .001

Table 9.
General linear models for two elements in a news article: Focused and Searching

	Variable	β	S.E.	t	Sig.	R^2
ImagexInfographic	(Intercept)	0.913	0.093	9.782	.000 ***	0.1737
	Image	-0.663	0.143	-4.642	.000 ***	
	Infographic	-0.210	0.143	-1.47	0.145	
	ImagexInfographic	NA	NA	NA	NA	
Image x Table	(Intercept)	0.657	0.0897	7.324	.000 ***	0.2191
	Image	-0.407	0.138	-2.946	0.004 **	
	Table	0.403	0.140	2.887	0.005**	
	ImagexTable	NA	NA	NA	NA	
TablexInfographic	(Intercept)	0.327	0.090	3.626	.000 ***	0.2094
	Table	0.732	0.140	5.217	.000 ***	
	Infographic	0.376	0.139	2.701	0.008**	
	TablexInfographic	NA	NA	NA	NA	

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article for 'Focused Attention and Searching' had very similar predictions as 'Focused Attention and Browsing'. For instance, *Image* (β= -.574, F[1, 105] = 19.49, p = .000), also indicated that image in the article predicts a lower visual attention score than text. Also, a statistical significance was shown for *Table* (β= .574, F[1, 105] = 19.11, p = .000) demonstrated that table in the article predicts a higher visual attention score than just text.

For two visual elements in a news article, all three combinations showed significant effects, but no interacting effects between the visual elements. As mentioned in 5.1.1. (pg. 35) this result is plausible because one element must be more salient than the other. The article with *Image & Infographic* showed

significant effects for *Image* only (β= -.663, F[2, 104] = 14.59, p = .000), indicating that image within an article with both image and an infographic predicted a lower visual attention score. Also, a non-significant trending in the predicted direction indicated a higher visual attention score for infographic than image; however, text-only article had a higher score than both. The article with *Image & Table* illustrated a significant effect for both *Image* (β= -.407, F[2, 104]= 14.59, p = .004) and *Table* (β= .403, F[2, 104]= 14.59, p = .005), demonstrating that having an image in an article with both image and table predicted a lower visual attention score, whereas having a table predicted a higher visual attention score. This suggests a significant trending in the predicted direction of having greater attention to table, text, than image, respectively. Finally, *Table & Infographic* showed a statistically significant effect for both *Table* (β= .732, F[2, 104]= 14.59, p = .000) and *Infographic* (β= .376, F[2, 104]= 14.59, p = .008), showing that a table in an article with both table and infographic predicted a higher visual attention score, as well as an infographic. This indicates that table and infographic have higher saliency than just text, signifying a predicted direction of having table, infographic, and text in the order of high to low saliency.

5.2.2. Information Recall

Descriptive statistics for the visual elements and its effects on Information Recall are shown in Table 10 for the context of 'Focused Attention and Searching'.

Table 10.
Descriptive Statistics of Visual Elements on information recall for 'Focused and Searching'

	Variable	*M*	*SD*	*Min*	*Max*
Focused Attention and Searching	Image	3.17	0.39	3.0	4.0
	Table	3.17	0.58	2.0	4.0
	Infographic	3.25	0.75	2.0	4.0
	TablexInfographic	2.58	0.67	2.0	4.0
	ImagexInfographic	2.42	0.79	1.0	4.0
	ImagexTable	3.36	0.67	2.0	4.0

The following Table 11 shows significant effects of *Infographic* for having one element with the news article. Table 12 shows significant effects of *Image & Infographic*, and *Image & Tabl*e for including two elements within the news article. The general linear model for *Image, Table*, and *Table & Infographic* had no significant effects.

Table 11.
General linear models for one element in a news article: focused and searching

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	2.96	0.11	27.53	.000***	
Image	0.01	0.17	0.08	0.937	-.012
(Intercept)	2.92	0.11	27.22	.000***	
Table	0.11	0.17	0.68	0.5	-.007
(Intercept)	3.128	.105	29.78	.000***	
Infographic	-0.378	.160	-2.368	.020*	-.065

*p <.05, ** p < .01, *** p < .001

Table 12.
General linear models for two elements in a news article: focused and searching

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
ImagexInfographic	(Intercept)	3.000	0.144	20.87	.000 ***	0.1271
	Image	0.261	0.206	1.269	0.208	
	Infographic	-0.083	0.203	-0.410	0.683	
	ImagexInfographic	-0.761	0.323	-2.357	0.021*	
ImagexTable	(Intercept)	3.042	0.149	20.42	.000 ***	0.06247
	Image	-0.250	0.211	-1.187	0.239	
	Infographic	-0.167	0.211	-0.791	0.431	
	ImagexTable	0.739	0.339	2.178	0.032*	
TablexInfographic	(Intercept)	3.000	0.147	20.48	.000 ***	0.094
	Table	0.261	0.209	1.246	0.217	
	Infographic	-0.167	0.207	-0.805	0.424	
	TablexInfographic	-0.511	0.329	-1.553	0.124	

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article indicated that there was a significant effect for *Infographic* (β = -.378, F[1, 81]= 5.609, p = .02) than no *Infographic* in the article, indicating that an infographic in an article predicts a significant decrease in information recall. For two visual elements in a news article, *Image & Infographic* (β= -.761, F[3, 79]= 3.835, p = .021) showed a significant effect on recall, illustrating that having both visual elements had a significant decrease in information recall than text. Also, a statistical significance was shown with *Image & Table* article (β= 0.739, F[3, 79]= 1.755, p = .032), demonstrating that an having both image and table in an article predicts a

significant increase in information recall. These results show that in general, having an infographic in an article decreases recall.

5.3. Divided Attention and Browsing

5.3.2. Visual Attention

Descriptive statistics for the visual elements and its effects on Visual Attention are shown in Table 13 for the context of 'Divided Attention and Browsing'.

Table 13.
Descriptive Statistics on visual attention for 'Divided and Browsing'

	Variable	*M*	*SD*	*Min*	*Max*
Divided Attention and Browsing	Text (control)	0.444	0.405	0.006	1.558
	Image	0.175	0.222	0.023	1.277
	Table	0.369	0.272	0.023	1.015
	Infographic	0.402	0.225	0.016	0.800

The following Table 14 shows significant effects of *Image* for having one element with the news article. *Table* did not have any significant effects, unlike the "Focused Attention" context in 5.1.1. and 5.1.2. Table 15 shows significant effects of *Image & Infographic, Image & Table*, and *Table & Infographic* for including two elements within the news article. The general linear model for *Infographic* had no significant effects.

Table 14.
General linear models for one element in a news article: 'Divided and Browsing'

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	0.394	0.029	13.47	.000 ***	

Image	-0.220	0.053	-4.158	.000 ***	.134
(Intercept)	0.309	0.031	9.93	.000***	
Table	0.060	0.057	1.06	0.292	0.001
(Intercept)	0.296	0.031	9.68	.000***	
Infographic	0.106	0.057	1.86	0.066	0.030

*p <.05, ** p < .01, *** p < .001

Table 15.
General linear models for two elements in a news article: 'Divided and Browsing'

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
ImagexInfographic	(Intercept)	0.389	0.039	10.09	.000 ***	
	Image	-0.214	0.059	-3.654	.000 ***	0.134
	Infographic	0.013	0.060	0.222	0.825	
	ImagexInfographic	NA	NA	NA	NA	
Image x Table	(Intercept)	0.413	0.039	10.63	.000 ***	
	Image	-0.239	0.059	-4.062	.000 ***	0.138
	Table	-0.044	0.059	-0.744	0.458	
	ImagexTable	NA	NA	NA	NA	
TablexInfographic	(Intercept)	0.243	0.040	6.148	.000 ***	
	Table	0.126	0.061	2.057	0.042*	0.066
	Infographic	0.159	0.062	2.571	0.011 *	
	TablexInfographic	NA	NA	NA	NA	

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article indicated that there was a significant effect for *Image* (β= -.022, F[1, 112]= 17.29, p = .000), demonstrating that image in the article predicts a lower visual attention score than text. *Table* and *Infographic* did not show any statistical significance, suggesting that the saliency of table and infographic did not have any difference when compared to text.

For two visual elements in a news article, all three combinations showed significant effects, but no interacting effects between the visual elements. The article with *Image & Infographic* showed significant effects for *Image* only (β= -.214, F[2, 111]= 8.596, p = .000), indicating that image in an article with both image and an infographic predicted a lower visual attention score than text. In other words, text had a higher saliency than image. The article with *Image & Table* illustrated a significant effect for *Image* only as well (β= -.239, F[2, 111]= 8.888, p = .000), very similar to Image and Infographic. This also demonstrated that an image in an article with both image and infographic predicted a lower visual attention score than text. The results suggest that for *Image & Infographic* and *Image & Table*, texts was more salient than any visual elements. On the other hand, *Table & Infographic* showed a statistically significant effect for both *Table* (β= .126, F[2, 111]= 3.895, p = .042) and *Infographic* (β= .159, F[2, 111]= 3.895, p = .011), showing that a table in an article with both table and infographic predicted a higher visual attention score, as well as an infographic. This indicates that table and infographic have higher saliency than text. Also, this signifies a predicted direction of having infographic, table, and text in the order of high to low saliency.

5.3.3. Information Recall

Descriptive statistics for the visual elements and its effects on Information Recall are shown in Table 16 for the context of 'Divided Attention and Browsing'.

Table 16.
Descriptive Statistics on information recall for 'Divided and Browsing'

	Variable	*M*	*SD*	*Min*	*Max*
Divided Attention and Browsing	Image	2.92	0.79	2.0	4.0
	Table	3.17	0.72	2.0	4.0
	Infographic	2.75	0.87	1.0	4.0
	TablexInfographic	2.5	0.67	1.0	3.0
	ImagexInfographic	2.25	0.62	1.0	3.0
	ImagexTable	2.58	1.00	1.0	4.0

The following Table 17 shows significant effects of *Infographic* for having one element with the news article. The general linear model for *Image, Table*, and all the combinations in articles with two elements had no significant effects. Appendix D includes the tables of non-significant model of two elements for reference.

Table 17.
General linear model for one element in a news article: divided and browsing

Variable	β	S.E.	t	Sig.
(Intercept)	2.83	0.117	24.3	.000 ***
Image	-0.250	0.178	-1.41	0.164
(Intercept)	2.71	0.118	23.0	.000 ***
Table	0.042	0.180	0.231	0.818
(Intercept)	2.896	0.114	29.78	.000 ***
Infographic	-0.396	0.175	-2.266	0.026*

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article indicated that there was a significant effect for *Infographic* ($\beta = -.396$, $F[1, 82] = 5.134$, $p = .026$) than no Infographic in the article, indicating that an infographic in an article predicts a significant decrease in information recall. As for the rest of the visual elements in articles with one element as well as two, there were no significant effects shown. This result demonstrates that in the context of Divided Attention and Browsing, no particular visual elements aided the recall of the information in the article. Appendix D includes the tables of the non-significant models for reference.

5.4. Divided Attention and Searching

5.4.1. Visual Attention

Descriptive statistics for the visual elements and its effects on Visual Attention are shown in Table 18 for the context of 'Divided Attention and Searching'.

Table 18.
Descriptive Statistics on visual attention for 'Divided and Searching'

	Variable	*M*	*SD*	*Min*	*Max*
Divided Attention and Searching	Text (control)	0.311	0.163	0.030	0.554
	Image	0.194	0.125	0.021	0.508
	Table	0.393	0.255	0.018	0.890
	Infographic	0.313	0.216	0.038	0.761

The following Table 19 shows significant effects of *Image & Table* for having one element with the news article. Table 20 shows significant effects of

Image & Infographic, *Image & Table,* and *Table & Infographic* for including two elements within the news article. The general linear model for Infographic had no significant effects.

Table 19.
General linear models for one element in a news article: 'Divided and Searching'

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	0.347	0.022	15.44	.000 ***	
Image	-0.153	0.041	-3.727	.000 ***	0.1078
(Intercept)	0.262	0.023	11.47	.000 ***	
Table	0.131	0.042	3.148	.002**	0.07934
(Intercept)	0.29606	0.02378	12.45	.000***	
Infographic	0.07297	0.14132	0.516	0.607	0.001318

*p <.05, ** p < .01, *** p < .001

Table 20.
General linear models for two elements in a news article: 'Divided and Searching'

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
ImagexInfographic	(Intercept)	0.372	0.030	12.58	.000 ***	
	Image	-0.178	0.045	-3.939	.000 ***	0.1209
	Infographic	-0.059	0.045	-1.307	0.194	
	ImagexInfographic	NA	NA	NA	NA	
Image x Table	(Intercept)	0.312	0.029	10.63	.000 ***	
	Image	-0.119	0.045	-2.637	0.009**	0.1323
	Table	0.081	0.045	1.794	0.075	
	ImagexTable	NA	NA	NA	NA	
TablexInfographic	(Intercept)	0.224	0.030	7.508	.000 ***	
	Table	0.170	0.046	3.718	.000 ***	0.1093
	Infographic	0.089	0.046	1.958	0.053	
	TablexInfographic	NA	NA	NA	NA	

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article indicated that there was a significant effect for *Image* (β= -0.153, , F[1, 115]= 13.89, p = .000), demonstrating that image in the article predicts a lower visual attention score than text. Also, a statistical significance was shown for *Table* (β= 0.131, F[1, 115] = 9.911, p = .000) indicating that including a table predicts a higher visual attention score than just text.

For two visual elements in a news article, all three combinations showed significant effects, but no interacting effects between the visual elements. The article with *Image & Infographic* illustrated similar results as 'Divided Attention and Browsing'. For example, significant effects for *Image* only (β= -.178, F[2, 114], 7.842, p = .000), indicated that image in an article with both image and an infographic predicted a lower visual attention score than text. Also, *Image & Table* illustrated a significant effect for Image as well(β= -0.119, F[2, 114]= 8.688, p = .009), demonstrating that an image in an article with both image and infographic predicted a lower visual attention score than text. The results suggest that for *Image & Infographic* and *Image & Table*, texts was more salient than any visual elements. On the other hand*, Table & Infographic* showed a statistically significant effect for *Table* (β= .170 , F[2, 114] = 6.995, p = .000) showing that a table in an article with both table and infographic predicted a higher visual attention score. This indicates that table has a higher saliency than text. However, *Infographic* had a marginally significant effect (β= .089 F[2, 114] = 6.995, p

= .053) signifying a predicted direction of having table, infographic, and text in the order of high to low saliency.

5.4.2. Information Recall

Descriptive statistics for the visual elements and its effects on Information Recall are shown in Table 21 for the context of 'Divided Attention and Searching'.

Table 21.
Descriptive Statistics o on information recall for 'Divided and Searching'

	Variable	*M*	*SD*	*Min*	*Max*
Divided Attention and Searching	Image	3.17	0.72	2.00	4.00
	Table	3.08	0.67	2.00	4.00
	Infographic	3.00	0.74	1.00	4.00
	TablexInfographic	2.83	0.83	2.00	4.00
	ImagexInfographic	2.00	0.85	1.00	4.00
	ImagexTable	3.31	0.63	2.00	4.00

The following Table 22 shows significant effects of *Table* for having one element with the news article. Table 23 shows significant effects of *Image & Infographic* for including two elements within the news article. The general linear model for Image, *Infographic, Image & Table,* and *Table & Infographic* in articles with two elements had no significant effects.

Table 22.
General linear models for one element in a news article: 'Divided and Searching'

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	2.792	0.132	21.22	.000 ***	

Image	0.046	0.199	0.232	0.817	-0.011
(Intercept)	2.604	0.127	20.51	.000 ***	
Table	0.477	0.193	2.478	0.015*	0.069
(Intercept)	2.959	0.128	23.15	.000 ***	
Infochart	-0.348	0.196	-1.772	0.08	0.036

*p <.05, ** p < .01, *** p < .001

Table 23.
General linear models for two elements in a news article: 'Divided and Searching'

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
ImagexInfochart	(Intercept)	2.6667	0.1693	15.75	.000 ***	
	Image	0.573	0.237	2.419	0.017*	0.1922
	Infochart	0.250	0.239	1.044	0.299	
	ImagexInfochart	-1.490	0.377	-3.952	0.000 ***	
Image x Table	(Intercept)	2.625	0.18029	14.56	.000 ***	
	Image	-0.04167	0.25496	-0.163	0.871	0.08411
	Table	0.33333	0.25496	1.307	0.195	
	ImagexTable	0.39103	0.39688	0.985	0.327	
TablexInfochart	(Intercept)	2.7083	0.1795	15.09	.000 ***	
	Table	0.4917	0.2513	1.957	0.0538	0.09224
	Infochart	-0.2083	0.2538	-0.821	0.4142	
	TablexInfochart	-0.1583	0.3997	-0.396	0.6931	

*p <.05, ** p < .01, *** p < .001

Results for one visual element in a news article indicated that there was a significant effect for *Table* (β = .4769, t(83) = -2.478, p = .015) than no *Table* in the article, indicating that a table in an article predicts a significant increase in information recall. For two visual elements in a news article, *Image & Infographic* (β= -1.490, t[81] = -3.952, p = .000) showed a significant effect on recall, illustrating that including both image and infographic in an article had a significant decrease in information recall.

5. Discussion

The goal of this study was to examine how the visual elements within news articles affect reader's visual attention and information recall based on four different contexts. With the measures for both visual attention and information recall, the study aimed to investigate the order of saliency for the visual elements in different context and observe the possibility of assigning a scoring value for automating visual news generation. In order to do so, the research conducted an experiment that set up the four contexts relevant to online news reading, and gathered quantified data on user's visual attention and information recall.

This discussion section addresses the major results and explanations of visual attention and information recall for each of the four contexts: *focused attention & browsing, focused attention* & *searching, divided attention & browsing,* and *divided attention & searching.* Then, this section will conclude with a discussion on the findings observed in all contexts.

5.1. Focused Attention and Browsing

In a situation where a reader was fully attending to an article and browsing information, combination of *Table & Infographic* or *Image & Table* indicated a definitive order of saliency. In both cases, *Table* was the definitive element that had a higher saliency over *Infographic* or *Image.* This indicates that readers noticed tables earlier and spent time processing the information comparatively more than infographics or images, and then attended to the rest of the text

afterwards. In fact, *Table* showed similar results across all contexts as well, which indicates that tables can be an effective visual element that can guide user's visual attention to information that needs to be emphasized. This result ties well with previous studies on newspaper design factors as well. According to Schumacher (2007), short texts like drop quotes, fact boxes, briefs, and teasers are all elements that stand out against the main content, thus are seen earlier and read for longer. Similarly, the design of *Table* presented in the experiment was organized into short alignments of text and bounding boxes which explains the higher saliency over the main text.

The findings for information recall in *Focused attention & Browsing* context did not show any significant results. A possible explanation for this result is due to the goals and expectations of reading an article in this situation (Grossberg, 1999). Because readers were passively seeking information without any particular intention in mind, they did not need to expand their cognitive effort into memory retention or recall.

In sum, the high saliency of *Table* used in this study demonstrated to be an element that captured reader's visual attention, but no effect on recall in a focused and browsing setting. The definitive order of saliency in *Table & Infographic* and *Image & Table* enables a scoring value that can be utilized in automatic visual news generation.

5.2. Focused Attention and Searching

The results of visual attention for *Focused Attention & Searching* were very similar with *Focused Attention & Browsing* condition. *Table* proved to be the effective element that captured reader's visual attention across all articles, and an order of saliency was established in *Table & Infographic* and *Image & Table* articles. In fact, the results for *Image, Table,* and *Infographic* alone were comparable to focused and browsing context as well. The similar results within the 'focused' group indicate that information behavior did not influence the effect of visual elements on reader's visual attention. A possible explanation for this result can be due to online reader behaviors that indicate a top-to-bottom or an F-Shaped pattern (Shrestha & Lenz, 2007). Studies like Shrestha & Lenz (2007) have observed that readers have a methodical pattern when readers engage in a reading behavior, a pattern difficult to be overridden by visual elements unless the elements exhibit high salient quality. In other words, although the visual elements used in this study showed differences in saliency, it was not enough to override the habitual reading patterns of the reader.

However, when the results of visual attention for 'focused' groups were compared against the 'divided' groups , there were notable differences. First, although the visual elements in the divided groups did show distinction in saliency, the differences were prominently lower than the 'focused' groups. Second, the order of saliency for *Divided & Browsing* and *Divided & Searching*

were different for some combination of elements, unlike the almost identical results of the 'focused' group. Explanation and speculation of the results for the 'divided' group will be discussed in 5.3 and 5.4.

On the other hand, the results of information recall in *Focused & Searching* context showed an observable difference compared to *Focused & Browsing* group. The result of *Image & Table* in an article indicated an increase in information recall only for *Focused Attention & Searching* context. This result is significant because out of all the comparisons between visual elements and its effects based on each context, this combination was the only one that provided a positive outcome on information recall. This result indicates that *Table* proved to be an effective visual element in recall especially in situations where readers were searching for specific information, as the effect of *Table* alone was also positive in 'Divided Attention & Searching' context. A further novel finding is that although *Image* alone did not have any particular effect in information recall in any of the contexts, and even had a negative effect when it was presented with an *Infographic*, the combination of image and table proved to have a positive effect. This suggests two things. First, table is a powerful visual element to be used in cases where people need to search for explicit information that having an image within the article did not deter the ability to recall information. Second, the absence of a comparatively complex figure such as an infographic might have helped the overall memory retention of a reader since the results of *Infographic*

alone suggest a higher cognitive effort to process. In other words, the combination of image and table was an appropriate selection of elements to achieve attentional efficiency that aided information processing.

Also, the effect of *Infographic* on information recall showed similar statistically significant results for the contexts 'Focused Attention & Searching' as well as 'Divided Attention & Browsing'. Planned comparisons revealed that including an infographic within a news article decreased the recall of information compared to text-only articles. This indicates that attributes of an infographic and the limited time to read the article may have prevented an accurate retention and recall of information. To elaborate, infographics used in this experiment, and many other infographics alike, contain shapes and colors that represent different types of information. Readers will often fixation on these infographics longer than other elements (Holmberg, 2004; Holmqvist & Wartenberg, 2005) in order to process the information. Also, time limit on viewing each article posed a certain amount of burden on readers, which also could have affected readers' ability to accurately recall information. Therefore, the comparatively complex nature of *Infographic* may have been the factor of decrease in recall.

To sum up, the article with *Image & Table* provided a definite order of saliency and effective information delivery within the *Focused & Searching* context, which can be used as a scoring value for automatic visual news generation. Another order of saliency that can be used as a scoring value was

Table & Infographic, although this combination of elements did not show any sigifnicant result in information recall.

5.3. Divided Attention and Browsing

The results of visual attention for *Divided Attention & Browsing* showed three notable observations that were prominently different from the rest of the contexts. First, *Table* did not show any significant effect only in this context. This suggest that when reader's attention is dispersed due to multitasking and he or she is browsing through the article, *Table* does not play a significant factor in grabbing readers' attention. A possible explanation for this is that the tables used in the experiment did not have any outstanding attributes that was salient enough to catch reader's attention when their attentional resource was limited. Also, the nature of 'browsing' behavior generally involves a methodical 'F-shaped' pattern which is difficult to be overridden by visual elements unless the elements exhibit high salient quality (Shrestha & Lenz, 2007).

Second, in the *Image* & *Table* combination, the result of visual attention did not show a significant trend in the order of *Table, Text,* and *Image* only in this context. A possible explanation for this result may be due to two reasons. First, the dispersion of attention due to the experimental setting, where the act of moving back and forth between the primary task (news reading) and the secondary task (digital coloring) had an impact on recording the eye-movement data to gather consistent results. Along with this, the nature of 'browsing'

behavior generally involves scanning the page in a F-shaped pattern (Shrestha & Lenz, 2007). Studies like Shrestha & Lenz (2007) have observed that readers have a methodical pattern when readers engage in a browsing behavior, a pattern difficult to be overridden by visual elements unless the elements exhibit high salient quality. This indicates that the saliency exhibited by the given visual elements in this study was not strong enough to catch reader's attention in a divided and browsing context.

Third, a notable result from observing the effect of *Table & Infographic* in an article is that both elements have higher saliency than text in all contexts. However, the level of saliency differed when comparing between 'focused' and 'divided' attentional states. For example, *Table* was the definitive element that had a higher saliency over *Infographic* for contexts that included 'Focused Attention'. This indicates that readers noticed tables earlier and spent more time processing the information comparatively more than infographics, and then attended to the rest of the text afterwards. The results for 'Divided Attention', on the other hand, had a very similar level of saliency between *Table* and *Infographic*. A possible explanation is that the visual attributes of *Table* and *Infographic* in this experiment did not vary sharp enough for distinct attentional selection in situations where readers' attentional resource was limited. However, it is important to note that the present evidence relies on the result of sporadic eye-movement recordings. Further investigation on manipulation of visual

attributes for each element might reveal specific factors that influenced the degree of saliency.

As for the results of information recall in *Divided Attention & Browsing* context, *Infographic* was the only element that showed a significant result. This indicates that including an *Infographic* within an article decreases the memory retention and recall compared to a text-only article. Previous study indicates that if there is too much information to interpret working memory decreases, thus affecting the ability to recall information (Miller, 1956). This result was similar in line with *Infographic* in *Focused Attention & Searching.* This suggests that no matter the attentional state or the information behavior of the reader, having an element with comparatively complex set of visuals hinders information recall.

In conclusion, when the reader's attention is dispersed due to dual tasking activities and they are browsing the news article, there were no optimal selection of visual elements to suggest a scoring value for automated visual news generation. This is because all the other cases of elements and combinations within the page did not have a definitive difference in saliency, nor a positive effect on information recall when including a visual element. A further study on different manipulations of visual elements and experimental setting may help expand the results.

5.4. Divided Attention and Searching

The results of visual attention for *Divided Attention & Searching* context showed similar outcomes as the 'focused' groups, although the mean difference between visual elements for *Table & Infographic* and *Image & Table* were minimal. For example, across all contexts, the combination of *Table & Infographic* on visual attention indicated that both *Table* and *Infographic* have higher saliency than text. However, the visual attention scores varied when comparing between 'Focused' and 'Divided' attentional states. In the 'focused' group, *Table* was the definitive element that had a higher saliency over *Infographic* because the mean difference between *Table, Infographic,* and *Text* were highly significant. This demonstrates that readers noticed tables earlier and spent more time processing the information comparatively more than infographics, and then attended to the rest of the text afterwards. The results of *Table* and *Infographic* for *Divided Attention & Searching*, on the other hand, had a very similar visual attention score, thus a comparable level of saliency between *Table* and *Infographic*. A possible explanation for this is that the visual attributes of *Table* and *Infographic* in this experiment did not vary sharp enough for distinct attentional selection in situations where readers' attention was dispersed. The same logic applies to *Image & Table* as well, where even though there was an order of saliency between the elements, the results were marginal because of the minimal difference between the mean scores of visual attention between *Image*

and *Table*. However, it is important to note that the present evidence relies on the result of sporadic eye-movement recordings. Further investigation on manipulation of visual attributes for each element might reveal specific factors that influenced the visual attention scores.

As for the results of information recall for *Divided Attention & Searching* context, *Table* was the only element that showed a positive recall score compared with the text-only article. In fact, this was the only context that *Table* displayed any significance in. This suggest that in situations where readers are multitasking and have a specific information to search for, table is an adequate element that improves attentional efficiency and effectively delivers the information. In addition, the effect of having both *Image & Infographic* in an article significantly decreased the information recall for both of the 'searching' contexts – 'Focused Attention and Searching' as well as 'Divided Attention and Searching'. This suggests that when readers have a specific goal to search for a particular information, having both image and infographic hindered the retention and recall of explicit information. This finding ties well with previous studies where limited cognitive resource impacts the amount of information human can store (Miller, 1956). If there is too much information to interpret, working memory decreases, thus affecting our ability to recall information. In other words, there were too many elements to process especially when the goal of the reader was finding a

specific information. Therefore, visual elements and must be kept simple within news articles for effective communication of the information.

5.5. All Contexts

This section discusses the results that were consistent through all contexts in terms of each visual element.

Image

The results for the effect of *Image* on visual attention indicated that across all four contexts, image does not have a higher saliency than text. This finding is in line with Leckner (2007) and Zambarbieri et. al (2008) where the results demonstrated that images and elements other than text received fewer fixations in a news article. The implication of this result highlights that image is often overlooked when reading an article, no matter what kind of situation a reader finds his or herself in. Another possible explanation for this result is that eye movements for reading behavior follow a habitually preferred path across a visual page, where readers are accustomed to graze over elements that complements textual information, such as an image (Josephson & Holmes, 2002; Melin, 1999). Moreover, earlier studies showed that the type of image influences whether or not the image will attract attention (Holmqvist and Wartenberg, 2005; Holmberg et. al, 2006). For example, in the study of comparing different types of photos in news articles, Adam et. al (2007) found that documentary photos received more

visual attention than staged photos. All in all, the result of this study is in line with earlier researches in newspaper factors in that although images might get earlier fixations, it receives fewer fixations overall and only complements textual information (Melin, 1999).

The analysis for the effect of *Image* on information recall did not have any significant effect across all contexts, which demonstrates two things. First, having an image within a news article does not aid in recalling specific information since image only complements the text with extra information about the content. Second, according to earlier studies, images, often in combination with text, offer an estimation and an insight to the content (Melin, 1999; Holmqvist and Wartenberg, 2005). In other words, image is not a major factor in recalling explicit information about the content; rather it is more effective in getting the overall essence of the article.

In sum, the results for visual attention and information recall demonstrate that image should be used as a complementary factor when constructing a news article, and not as a major element aimed to attract attention or deliver specific information.

Infographic

The analysis for the effect of *Infographic* on visual attention did not have any significant effect across all contexts, suggesting that the saliency of an infographic was not distinct enough to make a difference in reader's visual

attention. According to studies on management of attention in graphic displays, Rensink (2011) argues that attentional efficiency, or the minimum amount of effort expended in order make good use of limited amount of attention, is achieved when the saliency of non-essential graphical elements within the page are kept low as possible. This suggests that the saliency of infographic in this experiment was not high enough to be made as a distinction against text. Also, when comparing the result to those of older studies, it must be pointed out that elements like information graphics were fixated comparatively later than text and other visual elements (Holmberg, 2004; Holmqvist & Wartenberg, 2005). Notably, the research that Holmberg (2004) conducted were comparable to this study because it also used eye-tracking data to measure attention in an experimental setting. Holmberg's research demonstrated that articles with infographics were observed later, which they posited were due to infographics carrying complex information demanding more cognitive resources. They argued that because readers tend to maximize information intake during a limited period of time, news with more 'accessible content' was attended to first, then infographics were dealt with in the remaining time. From this stand point, the infographics in this experiment was harder to process than text for some participants; and as a result, did not show any significant effects in visual attention.

Image & Infographic

The article combination of *Image & Infographic* showed that image had a lower saliency than text across all contexts, in line with the results of having one image within an article. No significant results were found for infographic; however, a non-significant trend on *Infographic* indicated that infographics carry a higher saliency than image. Thus, the order of saliency would be text, infographic, and image across all contexts, although not statistically significant. A possible explanation for this result is that the saliency of an image is dependent upon various factors such as the type and content of the image, as well reader's habits such as skipping over images when reading an article; therefore the results of *Image* showed the lowest saliency in the article. *Infographic* on the other hand, is more salient than *Image* because it carries more information to interpret, thus more visual attention is required.

To sum up, the results of *Image & Infographic* showed a general trend of having text, infographic, and image as the order of saliency within the article across all contexts. The results suggest that the most critical information should be emphasized in text, than explained in infographics and image as supporting elements. However, because the results only showed a non-significant trend, a further research on the combination of these visual elements with more participants may expand the current results.

Table & Infographic

The results for the effect of *Table & Infographic* on information recall indicate that across all four contexts, having both elements within the article does not guide the recall of information. This finding is interesting to note because although the article with *Table* and *Infographic* did have higher saliency for readers to draw attention to more than text, the very fact that there were competing salient elements within the page attributed to non-significant results of information recall. Previous research on attentional efficiency have noted that in order to effectively deliver information in minimum amount of time, the saliency of 'nonessential graphical elements' should as low as possible (Rensink, 2011). This implies that having two visual elements that carry relatively similar saliency within the page require more effort from the readers to process the information, and thus impacting the memory retention and information recall.

6. Conclusion and Future Work

This study examined the effects of visual elements on reader's visual attention and information recall to investigate the possibility of assigning scoring values that can be applied in automating visual news generation. Observing the effect of visual elements based on contexts enabled an in-depth look into the degree of its influence, allowing for a more detailed explanation on why certain elements were appropriate or inadequate in each situations. In addition, this study proved that we can specify the hierarchy between visual elements by measuring the saliency score with visual attention and information recall. In turn, each context provided a range of different scores for visual attention and information recall, which also provided a possibility in scoring values for automatic visual news generation. Not only that, this study employed a new calculation of 'visual attention', which endowed a more suitable measure of visual saliency in an information presentation domain. Most of the past research in newspaper design studies that used eye-tracking methods have simply measured 'saliency' by operationalizing it as 'time to first fixation' or 'total fixation duration'. However, saliency in this study was defined and measured as 'visual engagement' that encompassed not just early fixations but how much visual information was processed and stored in our memory.

The results of this study also contributed to the general knowledge of visual elements within news articles. For example, the visual elements that were thought to exhibit higher saliency and better information recall do in fact depend on the

different contexts that readers were in. *Infographic*, which are often thought to be more salient among textual elements were actually cognitively demanding and did not show much influence especially in divided attentional situations. *Image,* contrary to certain studies, have shown a lower saliency and recall throughout the contexts. This implied that *Image* didn't carry enough significant information to be thought as visually engaging, especially in the contexts of reading a news article. Finally, *Table* was the element that had the highest score of visual attention and information recall, indicating a simple tabular chart can be visually salient and attentionally efficient especially in searching contexts.

Despite these contributions, this study was subjected to limitations due to the nature of the experiment. First, the visual elements used in this study were limited in that it was designed with fixed visual attributes. In other words, local factors such as color, line, typography, shape, etc. could have also been a contributing factor of user's visual attention and recall. Second, the type of image used were also fixed, which could have influenced the results. Therefore, further research examining more variations of visual attributes on each of these elements and other combinations of elements may expand the current results. Albeit these limitations, however, this research presents novel findings that are noteworthy to be utilized in automating the process of selecting visual elements. Therefore, the next step in the research would be to apply the saliency scores observed in this study to an actual automatic visual news generation system.

In sum, this study was able to present not only a methodology that can be utilized in implementing visual elements when developing automating visual news generation systems, but a general finding for the effect of visual elements that can give valuable insights to visual designers and developers who create online news contents as well.

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Appendix A

Seven articles with visual elements that were used in the experiment

1. Text only

오늘의 날씨 뉴스

2018년 9월 22일 4:00 AM

본격적인 추석 연휴 첫날이자 토요일인 22일은 아침까지 내륙을 중심으로 안개가 짙게 끼는 곳이 있고, 동해안을 비롯해 일부 중부지방에는 새벽까지 가끔 빗방울이 떨어질 전망이다. 아침 일찍 귀성길에 오를 경우 교통안전에 각별히 주의를 기울여야 한다.

토요일 오후는 전국에 화창하고 맑은 가을 날씨가 전망된다. 이날 중국 북부지방에 있는 고기압의 영향으로 전국이 대체로 맑겠다.

아침 최저기온은 15~20도로 평년 수준보다 조금 낮게 예상됐다. 낮 최고기온은 24~29도로 전날보다 5~6도가량 높겠다. 일교차가 크므로 건강관리에 신경을 써야 한다.

지역별 아침 최저기온은 서울/경기 15도, 대전 18도, 대구 18도, 부산 18도, 광주 17도, 제주 20도로 예보됐다. 낮 최고기온은 서울 24도, 대전 27, 대구 27도, 부산 28도, 광주광역시 27도, 제주 29도로 예상된다.

미세먼지 농도는 전 권역에 '보통' 수준으로 예보됐다. 다만 국외 미세먼지 유입과 대기 정체로 남부지방 일부는 밤에 미세먼지 농도가 조금 올라가겠다.

'이 기사는 서울대학교 HCI+D랩에서 개발한 기사 작성 알고리즘 로봇이 작성한 기사합니다.'
robot@weathernews.co.kr

2. Text and Image

오늘의 날씨 뉴스

2018년 1월 15일 6:00 AM

오늘 (15일) 올겨울 들어 가장 매서운 한파가 몰아칠 것으로 예보됐다. 서울과 인천, 경기, 강원, 충청에는 23일 오후 9시 기준으로 한파주의보가 내려졌다. 한파 경보는 영하 15도 이하 기온이 이틀 이상 지속할 것으로 예상될 때 발령된다.

가축의 동사, 비닐하우스 작물 피해, 수도관 동파 등 추위로 인한 피해가 없도록 각별히 유의해야 한다고 기상청은 당부했다.

지역별 최저 기온은 서울/경기 영하 22도, 광주 영하 21, 대전 영하 18도, 대구 영하 18도, 부산 영하 17도, 제주 영하 22도로 출발해서 한낮에는 서울/경기 영하 12도, 광주 영하 10도, 대전 영하 6도, 대구 영하 6도, 부산 영하5도, 제주는 영하10까지 오를 것으로 보인다.

전국은 대체로 흐리겠고, 서울과 경기도인 수도권 지역은 흐리고 구름이 많겠다.

미세먼지 농도는 전 권역에서 '좋음' 수준으로 예상됐다.

'이 기사는 서울대학교 HCI+D랩에서 개발한 기사 작성 알고리즘 로봇이 작성한 기사합니다.'
robot@weathernews.co.kr

3. Text with Table

오늘의 날씨 뉴스

2018년 8월 27일 8:00 AM

월요일인 27일 전국적으로 비가 내리며 일부 지역에서는 호우주의보가 내려질 전망이다. 다음 주 내내 전국 대부분 지역에서 장마와 비슷한 양상으로 비가 내릴 것으로 보인다.

전국 예상강수량	
서울 / 경기	80~150mm
광주	30~80mm
대전	30~80mm
대구/ 부산	30~80mm
제주도	20~70mm

27일 전국 아침 최저기온은 17~25도, 낮 최고기온은 23~32도로 예보됐다. 기록적인 폭염이 물러나고 선선한 날씨가 이어질 전망이다.

미세먼지 농도는 전국적으로 '매우 좋음' 수준을 보이겠다.

지역별 아침 최저기온은 서울 21도, 대전 21도, 대구 20도, 부산 25도, 광주 24도, 제주 26도로 예보됐다. 낮 최고기온은 서울 27도, 대전 28, 대구 29도, 부산 29도, 광주 광역시 29도, 제주 32도로 예상된다.

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robot@weathernews.co.kr

4. Text with Infochart

오늘의 날씨 뉴스

2018년 10월 10일 8:00 AM

오늘 (10일) 의 서울/경기 아침기온은 17도로 출발하지만 한낮에는 27도 까지 오르면서 기온차가 10도 안팎으로 크게 벌어지겠다.

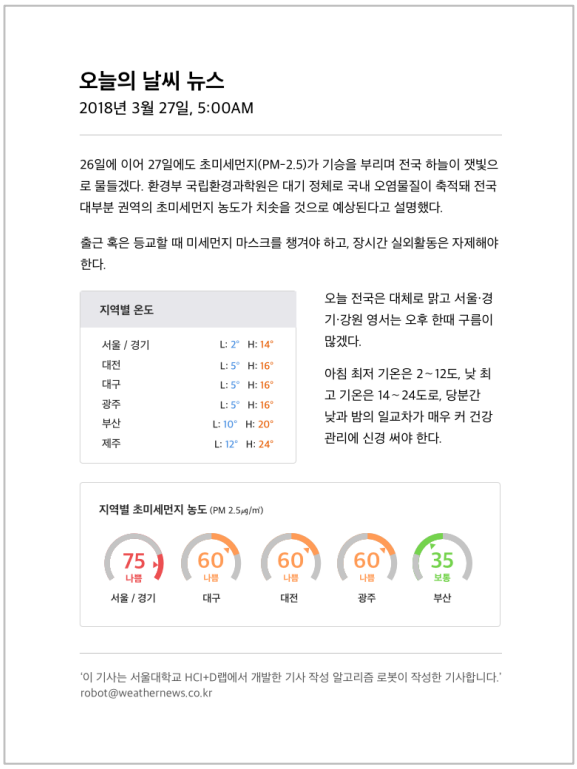
자외선의 강도에 따라 피부 등에 미치는 영향을 지수화한 것이 총 자외선지수다. 자외선지수가 보통(3~5)일 때는 외출 시 모자와 선글라스를 쓰며 자외선 차단제를 발라야 한다.

지역별 최저 기온은 서울/경기 17도, 광주 18, 대전 18도, 대구 19도, 부산 19도, 제주 20도로 출발해서 한낮에는 서울/경기 27도, 대전 27도, 대구와 광주 28도, 부산 29도, 제주 30까지 오르겠다.

미세먼지 농도는 서울/경기 지역 '좋음', 광주 '좋음', 대전 '좋음' 이며, 그 밖의 권역은 '좋음' ~ '보통' 수준을 보이겠다.

'이 기사는 서울대학교 HCI+D랩에서 개발한 기사 작성 알고리즘 로봇이 작성한 기사합니다.'
robot@weathernews.co.kr

5. Text with Table and Infochart



오늘의 날씨 뉴스

2018년 3월 27일, 5:00AM

26일에 이어 27일에도 초미세먼지(PM-2.5)가 기승을 부리며 전국 하늘이 잿빛으로 물들겠다. 환경부 국립환경과학원은 대기 정체로 국내 오염물질이 축적돼 전국 대부분 권역의 초미세먼지 농도가 치솟을 것으로 예상된다고 설명했다.

출근 혹은 등교할 때 미세먼지 마스크를 챙겨야 하고, 장시간 실외활동은 자제해야 한다.

지역별 온도

서울 / 경기	L: 2°	H: 14°
대전	L: 5°	H: 16°
대구	L: 5°	H: 16°
광주	L: 5°	H: 16°
부산	L: 10°	H: 20°
제주	L: 12°	H: 24°

오늘 전국은 대체로 맑고 서울·경기·강원 영서는 오후 한때 구름이 많겠다.

아침 최저 기온은 2~12도, 낮 최고 기온은 14~24도로, 당분간 낮과 밤의 일교차가 매우 커 건강 관리에 신경 써야 한다.

지역별 초미세먼지 농도 (PM 2.5㎍/㎥)

서울 / 경기	대구	대전	광주	부산
75 나쁨	60 나쁨	60 나쁨	60 나쁨	35 보통

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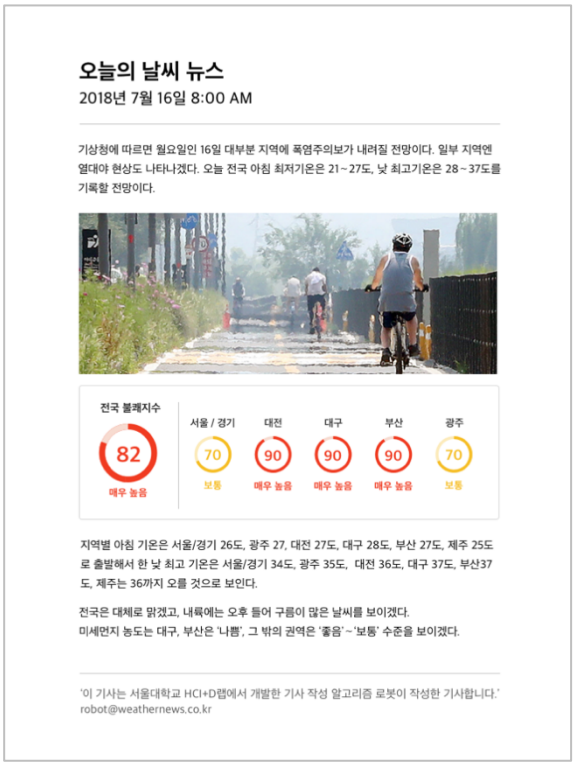
robot@weathernews.co.kr

6. Text with Image and Infochart



오늘의 날씨 뉴스

2018년 7월 16일 8:00 AM

기상청에 따르면 월요일인 16일 대부분 지역에 폭염주의보가 내려질 전망이다. 일부 지역엔 열대야 현상도 나타나겠다. 오늘 전국 아침 최저기온은 21~27도, 낮 최고기온은 28~37도를 기록할 전망이다.

전국 불쾌지수

82 매우 높음

서울 / 경기	대전	대구	부산	광주
70 보통	90 매우 높음	90 매우 높음	90 매우 높음	70 보통

지역별 아침 기온은 서울/경기 26도, 광주 27, 대전 27도, 대구 28도, 부산 27도, 제주 25도로 출발해서 한 낮 최고 기온은 서울/경기 34도, 광주 35도, 대전 36도, 대구 37도, 부산37도, 제주는 36까지 오를 것으로 보인다.

전국은 대체로 맑겠고, 내륙에는 오후 들어 구름이 많은 날씨를 보이겠다.
미세먼지 농도는 대구, 부산은 '나쁨', 그 밖의 권역은 '좋음'~'보통' 수준을 보이겠다.

'이 기사는 서울대학교 HCI+D랩에서 개발한 기사 작성 알고리즘 로봇이 작성한 기사입니다.'
robot@weathernews.co.kr

7. Text with Image and Table

오늘의 날씨 뉴스

2017년 12월 31일 5:00 AM

일요일인 오늘, 올겨울 처음으로 폭설이 내릴 것으로 예보됐으며 일부 지역에는 폭설주의보가 발령될 예정이다. 국민행동요령에 따르면 폭설주의보는 24시간 새로 내려 쌓인 눈의 깊이가 5cm 이상일 때 내려지는 것이다.

지역별 적설량	
서울 / 경기	15~20 cm
대전	5~10 cm
대구	5~10 cm
광주	5~10 cm
부산	5~10 cm
제주	1~5 cm

오늘 전국 아침 최저기온은 전날보다 5~6도가량 낮은 영하 20도~영하 10도 수준으로 예상된다. 낮 최고기온도 전날보다 1~2도 낮은 영하 12도~영하 5도로 전망됐다.

지역별 최저 기온은 서울/경기 영하 20도, 광주 영하 18, 대전 영하 15도, 대구 영하 15도, 부산 영하 10도, 제주 영하 10도로 출발해서 한낮에는 서울/경기 영하 12도, 광주 영하 8도, 대전 영하 6도, 대구 영하 6도, 부산 영하 5도, 제주는 영하 5도까지 오를 것으로 보인다.

미세먼지 농도는 전 권역에서 '좋음' 수준으로 예상됐다.

'이 기사는 서울대학교 HCI+D랩에서 개발한 기사 작성 알고리즘 로봇이 작성한 기사합니다.'
robot@weathernews.co.kr

Appendix B.

Information recall questionnaires used in the experiment. The symbols in each set of questionnaire represent different types of news articles presented to the participant. Symbols were used to randomize the order of the articles without the participant noticing.

다음은 (X) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (X)의 내용을 떠올려 보십시오. 기사 (X)의 내용 중 전국 하늘 상태는 무엇이었습니까?
   ① 맑음 ② 구름 조금 ③ 구름 많음 ④ 구름 많고 비 ⑤ 비

2. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (X) 의 내용 중 전국 최저기온은 무엇이었습니까?
   ① 10~15 도 ② 15~20 도 ③ 20~25 도 ④ 30~35 도 ⑤ 35~40 도

4. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사 (X)의 내용 중 전국 미세먼지 지수는 무엇이었습니까?
   ① 매우 나쁨 ② 나쁨 ③ 보통 ④ 좋음 ⑤ 매우 좋음

6. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (X)의 내용 중 어떤 이유로 건강관리에 신경을 써야 된다고 하였습니까?

① 건조한 날씨 ② 일교차가 큼 ③ 폭염 ④ 한파 ⑤ 자외선 지수가 매우 높음

8. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Δ) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Δ) 의 내용을 떠올려 보십시오. 기사 (Δ)의 내용 중 일부 지역에 어떤 주의보가 발령됐습니까??

① 폭설주의보 ② 미세먼지 주의보 ③ 호우주의보 ④ 폭염주의보 ⑤ 한파주의보

2. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Δ)의 내용 중 서울-경기도 지역의 최저 기온은 무엇이었습니까?

① -10 도 ② -12 도 ③ -15 도 ④ -22 도 ⑤ -24 도

4. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사 (Δ)의 내용 중 어떠한 피해가 없도록 특히 유의해야 한다고 하였습니까?

① 교통사고 ② 침수 피해 ③ 산불 ④ 수도관 동파 ⑤ 낙뢰 사고

6. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Δ)의 내용 중 전국의 하늘상태는 무엇이었습니까?
① 맑음 ② 대체로 흐림 ③ 흐림 ④ 비 ⑤ 비 온 뒤 맑음

8. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Π) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Π)의 내용을 떠올려 보십시오. 기사 (Π)의 내용 중 어떤 지역에 가장 많은 비가 내릴 예정이었습니까?
① 서울 / 경기 ② 광주 ③ 대구 ④ 대전 ⑤ 부산 ⑥ 제주

2. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Π)의 내용 중 일부 지역에 어떤 주의보가 발령됐습니까??
① 폭설주의보 ② 미세먼지 주의보 ③ 호우주의보 ④ 폭염주의보 ⑤ 한파주의보

4. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. . 기사 (Π)의 내용 중 어떤 날씨가 이어지리라 전망했습니까?
① 일교차가 큰 날씨 ② 선선한 날씨 ③ 매우 더운 날씨 ④ 건조한 날씨
⑤ 습한 날씨

6. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Π)의 내용 중 전국 아침 최저 기온은 무엇이었습니까?

① 10~16 도 ② 15~21 도 ③ 17~25 도 ④ 26~31 도 ⑤ 28~34 도

8. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Φ) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Φ)의 내용을 떠올려 보십시오. 기사 (Φ)의 내용 중 전국 자외선 지수는 무엇이었습니까?

① 매우 낮음 ② 낮음 ③ 보통 ④ 높음 ⑤ 매우 높음

2. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Φ)의 내용 중 서울/경기 지역의 기온 차는 얼마만큼 벌어진다고 하였습니까?

① 5 ② 10 ③ 15 ④ 20 ⑤ 25

4. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사 (Φ)의 내용 중 서울/경기 지역의 자외선 지수는 무엇이었습니까?

① 매우 낮음 ② 낮음 ③ 보통 ④ 높음 ⑤ 매우 높음

6. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Φ)의 내용 중 광주 지역의 미세먼지 지수는 무엇이었습니까?

① 매우 나쁨 ② 나쁨 ③ 보통 ④ 좋음 ⑤ 매우 좋음

8. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Σ) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Σ)의 내용을 떠올려 보십시오. 기사 (Σ)의 내용 중 어느 지역이 가장 낮은 최저/최고 온도로 예상되었습니까?

① 서울 / 경기 ② 광주 ③ 대구 ④ 대전 ⑤ 부산 ⑥ 제주

2. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Σ)의 내용 중 서울/경기 지역의 초미세먼지 농도는 무엇이었습니까?

① 매우 나쁨 ② 나쁨 ③ 보통 ④ 좋음 ⑤ 매우 좋음

4. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사(Σ)의 내용 중 부산 지역의 초미세먼지 농도는 무엇이었습니까?

① 매우 나쁨 ② 나쁨 ③ 보통 ④ 좋음 ⑤ 매우 좋음

6. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Σ)의 내용 중 전국의 하늘상태는 무엇이었습니까?

① 맑음 ② 대체로 맑음 ③ 흐림 ④ 비 ⑤ 비 온 뒤 맑음

8. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Ω)뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Ω)의 내용을 떠올려 보십시오. 기사 (Ω)의 내용 중 전국 불쾌 지수는 무엇이었습니까?

① 매우 낮음 ② 낮음 ③ 보통 ④ 높음 ⑤ 매우 높음

2. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Ω)의 내용 중 일부 지역에 무슨 현상이 나타난다고 하였습니까?

① 서리 ② 안개 ③ 황사 ④ 열대야 ⑤ 우박

4. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사 (Ω)의 내용 중 서울/경기 지역의 불쾌 지수는 무엇이었습니까?

① 매우 낮음 ② 낮음 ③ 보통 ④ 높음 ⑤ 매우 높음

6. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Ω)의 내용 중 제주 지역의 최고 온도는 무엇이었습니까?

① 34 ② 36 ③ 37 ④ 38 ⑤ 40

8. 귀하는 다음 문장에 얼마나 동의하십니까? “나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다”

① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

다음은 (Ψ) 뉴스 기사 내용에 대한 질문입니다. 아래 질문에 각각 체크해 주시기 바랍니다.

1. 기사 (Ψ)의 내용 중 어느 지역에 가장 적은 눈이 내릴 예정입니까?
   ① 서울 / 경기 ② 광주 ③ 대구 ④ 대전 ⑤ 부산 ⑥ 제주

2. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

3. 기사 (Ψ)의 내용을 떠올려 보십시오. 기사 (Ψ)의 내용 중 일부 지역에 어떤 주의보가 발령됐습니까?
   ① 폭설주의보 ② 미세먼지 주의보 ③ 호우주의보 ④ 폭염주의보 ⑤ 한파주의보

4. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

5. 기사 (Ψ)의 내용 중 서울/경기 지역의 적설량은 무엇이었습니까?
   ① 1~5 cm ② 5~10 cm ③ 10~15 cm ④ 10~20 cm ⑤ 15~20 cm

6. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

7. 기사 (Ψ)의 내용 중 전국 지역의 미세먼지 지수는 무엇이었습니까?
   ① 매우 나쁨 ② 나쁨 ③ 보통 ④ 좋음 ⑤ 매우 좋음

8. 귀하는 다음 문장에 얼마나 동의하십니까? "나는 위의 질문에 대해 매우 정확하게 대답할 수 있었다"
   ① 전혀 그렇지 않다 ② 그렇지 않다 ③ 보통이다 ④ 그렇다 ⑤ 매우 그렇다

Appendix C.

General linear model for one element articles in information recall, Focused Attention & Browsing

Variable	β	*S.E.*	*t*	*Sig.*	R^2
(Intercept)	2.729	0.131	20.91	.000***	
Image	0.160	0.199	0.801	0.425	0.008
(Intercept)	2.667	0.129	20.65	.000***	
Table	0.306	0.197	1.549	0.125	0.028
(Intercept)	2.938	0.129	22.79	.000***	
Infographic	-0.326	0.197	-1.658	0.101	0.032

General linear model for two element articles in information recall, Focused Attention & Browsing

	Variable	β	*S.E.*	*t-*	*Sig.*	R^2
ImagexInfographic	(Intercept)	2.792	0.183	15.28	.000 ***	
	Image	0.292	0.259	1.129	0.262	0.051
	Infographic	-0.125	0.259	-0.484	0.630	
	ImagexInfographic	-0.458	0.409	-1.122	0.265	
Image x Table	(Intercept)	2.500	0.183	13.66	.000 ***	
	Image	0.333	0.259	1.288	0.201	0.048
	Infographic	0.458	0.259	1.771	0.080	
	ImagexTable	-0.292	0.409	-0.713	0.478	
TablexInfographic	(Intercept)	2.708	0.181	14.97	.000 ***	
	Table	0.458	0.256	1.792	0.077	0.070
	Infographic	-0.083	0.256	-0.326	0.745	
	TablexInfographic	-0.500	0.405	-1.236	0.220	

Appendix D.

General linear model for two element articles in information recall, Divided Attention & Browsing

	Variable	β	*S.E.*	*t*	*Sig.*	R^2
	(Intercept)	3.04167	0.16029	18.975	.000***	
	Image	-0.29167	0.22669	-1.287	0.2019	0.09815
ImagexInfographic	Infographic	-0.41667	0.22669	-1.838	0.0698	
	ImagexInfographic	-0.08333	0.35843	-0.232	0.8167	
	(Intercept)	2.833	0.1668	16.99	.000***	
	Image	-0.25	0.2359	-1.06	0.292	0.0235
Image x Table	Table	-6.1E-16	0.2359	0	1	
	ImagexTable	4.05E-16	0.373	0	1	
	(Intercept)	3.04167	0.16029	18.975	.000***	
	Image	-0.29167	0.22669	-1.287	0.2019	0.09815
ImagexInfographic	Infographic	-0.41667	0.22669	-1.838	0.0698	
	ImagexInfographic	-0.08333	0.35843	-0.232	0.8167	

국문 초록

최근 기계 학습 및 자연어 처리 기술이 발달하며 인공지능이 자동으로 뉴스 기사를 생산하는 '로봇 저널리즘' (Robot Journalism 혹은 Algorithmic Journalism)이 새롭게 연구되어야 할 주제로 주목받고 있다. 로봇 저널리즘은 자동화된 뉴스 생성 시스템을 통해 텍스트 기반 뉴스 기사를 실시간으로 제작하고 대중들에게 게재하는 알고리즘을 일컫는다. 하지만 텍스트 기반 기사는 현재 뉴스를 소비하는 독자 패턴에 맞지 않는다. 현재 뉴스 독자들은 간결하고 이미지 지향적인 기사를 선호하는 경향이 있고, 실제 현재 언론사에서는 이미지, 인포그래픽, 도표 등 다양한 시각적 요소를 포함한 뉴스 기사를 생성하고 있다. 그러나 다양한 시각적 요소를 기존에 있는 로봇 저널리즘 알고리즘에 적용하려면 각종 정보 유형에 적절한 시각적 형태가 무엇인지 자동으로 파악할 수 있는 채점 방법(scoring method)가 필요하다. 현재 게재되고 있는 시각적 뉴스 기사는 그래픽 디자이너 혹은 편집자의 충분한 경험과 지식을 바탕으로 다양한 기사 내용에 적절한 시각적 요소가 결정된다. 하지만 자동 뉴스 생성 시스템에 시각적 요소를 포함하게 되면 각 상황마다 적절한 시각적 요소를 결정할 수 있는 디자이너가 없기 때문에, 이 과정을 자동화할 때 다양한 컨텍스트에 적절한 시각적 요소를 평가할 수 있는 채점 방법이 필요한 것이다.

기사에 포함되는 시각적 요소는 텍스트와 달리 다양한 속성 (i.e. 색깔, 크기, 모양, 등)을 통해 시각적 현저성 정도 (visual saliency level)를 구축하게 되는데, 이때

시각적 현저성은 제시되는 정보에 시각적 계층 구조(visual hierarchy)를 만들어 사용자의 주의와 정보회상에 영향을 미치게 된다. 따라서 이 연구에서는 시각적 요소가 사용자의 주의와 정보 회상에 미치는 영향을 관찰함으로써 뉴스 기사에 포함된 시각적 요소를 다양한 컨텍스트에 대비해 시각적 현저성 정도로 수치화하여 자동 뉴스 생성 과정에 필요한 채점 방법을 제시하였다. 그 결과, 각 컨텍스트 마다 사용자의 주의 및 정보 회상이 다양한 현저성을 나타내었다. 이러한 결과는 시각적 요소의 현저성을 다양한 컨텍스트에 대비해 관찰하게 되면 자동 뉴스 생성에 필요한 수치가 생성된다는 뜻이며, 이 수치는 향후 시각적 요소를 자동화에 포함할 때 필요한 채점 방법의 가능성을 시사한다.

주요어 : 시각적 요소, 시각적 주의, 정보 회상, 로봇 저널리즘, 자동 뉴스 생성

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