Cognitive Information Theories of Psychology and Applications with Visualization and HCI Through Crowdsourcing Platforms

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1 Introduction

This chapter introduces information processing perspectives from cognitive psychology, providing historical background content where it might prove useful. The hope is that this will provide readers enough of an understanding of psychology perspectives, theories, and methods that they can better apply crowdsourcing methods to understand the cognitive outcomes of interaction within visualization environments and other computer interfaces.

Readers who are interested in a comprehensive understanding of cognitive psychology theory and methods would do well to refer to one of the many textbooks or online resources (such as the Noba Project[1]) on psychology history, theory and methods. Here we will limit ourselves to touching on key perspectives with an emphasis on the diversity of approaches that have been used to study cognition.

2 Introduction to Psychology and Its Subdomains

It is important to understand that the field of cognitive psychology did not emerge from a single methodological or conceptual framework. Rather, it grew out of a number of different approaches to understand the nature of mental life. Some theoretical work in early psychology was not based on scientific observation at all, but on the clinical work of trained practitioners through subjective introspection, and without objective verification. Other researchers developed lines of inquiry based on methodological approaches from scientific disciplines such as chemistry, biology, physics, and engineering [24]. This diversity of approaches led to much disagreement as to what methods would be most effective, and what kind of theory would provide the best understanding of human cognition.

[1] http://novaproject.com last accessed 14 Jun 2017.

D. Archambault et al. (Eds.): Evaluation in the Crowd, LNCS 10264, pp. 139–153, 2017.
DOI: 10.1007/978-3-319-66435-4_6

2.1 Structrualism

One of the first conceptual approaches to psychology, developed in the early 1900s, was Structuralism [71]. This was founded in part by Wilhelm Wundt and later developed by E. Bradford Titchener. Structuralism was in part inspired by methodological advancements in the field of chemistry. In a way analogous to research on chemical compounds, Structuralists aimed to use introspective methods to identify and catalog a diverse set of mental properties, and then to discover how those properties combined to make up more complex mental operations. When applied by chemists, this approach produced a manageable set of elements and compounds. The same approach taken by Structuralist researchers led to claims of at least 40,000 elements of sensation alone [71]. However, the work drew criticism from contemporaries such as William James, who claimed that the profusion of elements was the result of the "psychologist's fallacy" of introspective methods. He concluded that introspection could not be used to discover elements of sensation and perception without distortion [36].

2.2 Functionalism

Another contemporary movement in psychology was the Functionalist movement. Functionalists examined the role of mind, or mental activity, in the life of an organism [8]. This approach drew from Darwin's theory of natural selection. Early Functionalists aimed to explore consciousness [36] through studying mental operations, and to identify psychophysical relations [1] that transform physical phenomena (e.g. an image projected on the retina) with their psychological outcomes (e.g. the perception of the stimulus).

2.3 Gestalt Psychology

A third contemporary approach, Gestalt psychology, was inspired by the physics of the day. Gestalt psychologists employed third-person phenomenological inquiry to discover principles of perceptual organization [75]. One driving idea behind this methodological approach was the insight that mental properties combine to create something new in the same way that physical particles organize into new wholes. Wertheimer put it this way, "I stand at the window and see a house, trees, sky. Theoretically, I might say there were 327 brightnesses and nuances of color. Do I have '327'? No. I have sky, house, and trees" [75]. As this quote suggests, Gestalt psychologists were aware of the challenges of identifying the units and levels of mind that could be empirically investigated. From the Gestalt perspective, our perception of events in the world is better explained by regularities in the environment itself rather than by an information processing method.

2.4 Behavioral Psychology

These competing ontologies made it difficult for a unified approach to understanding human cognition to emerge. Lacking any common ground of concepts, reconciling structuralism and functionalism proved impossible.

A different approach altogether was taken by behavioral psychologists, who avoided conflicts between competing ontologies, arguing that any conceptual approach would have to be based on subjective evidence and so fail to rise to the level of a true science. In order to avoid what they considered to be a subjective approach to science Behaviorists instead chose to empirically study actions, i.e., what people and animals do in response to different environmental situations (e.g. [51]).

Behavioral psychology became the dominant approach of psychology in the 1950s with its use of classical and operant conditioning methods to understand human and animal behavior. Classical conditioning experiments [51], demonstrated that through pairing the sound of a bell with food, associative learning could occur, a process now called classical conditioning. To demonstrate this, Pavlov measured the levels of saliva a dog produced when exposed to these stimuli. With the presence of food the dog would salivate, and after some training the food was removed and the dog would continue to salivate on the sound of the bell. This classically conditioned response coupled the presence of food with the sound of the bell, leading to the same result regardless of which stimulus was used. Skinner [23], expanded this work in an approach called operant conditioning. Operant conditioning proposed that any behavior which led to a pleasant outcome was likely to be repeated, and any behavior which led to an unpleasant outcome would be less likely to be repeated. Individual behaviors that led to positive outcomes could be combined, resulting in complex patterns of behavior that could be reliably produced in animals and humans.

Behaviorism produced many interesting findings. However, by the late 1960s it was no longer the dominant theory in psychology. The challenge came from studies demonstrating characteristics of behavior that were not easily explained by conditioning. Notable among these was Chomsky's transformative generative grammar, as described in his book 'Syntactic Structures' published in 1957 [10]. Chomsky argued that Skinner's operant conditioning was not adequate to explain the emergence of language. Instead, there were innate components to language in the form of a universal grammar. Chomsky suggested that all cultures, even in remote regions, have the same basic components of language such as verbs and nouns, and that language could be generated in an almost infinite amount of ways. Without the conceptual core of universal grammar it would be unlikely that language could be explained through conditioning alone (see [17], for a more complete historical perspective).

2.5 The Beginnings of Cognitive Psychology

Through challenges such as Chomsky's, it became apparent that understanding cognition would require researchers to study mental representations and ways in which they were generated, processed, stored and recalled. Thus Cognitive Psychology gradually replaced Behaviorism as the dominant paradigm of psychology, and it was then incorporated in early Human-Computer Interaction (HCI). It remains central to HCI and visualization research today.

Cognitive psychology was used by Ulric Neisser in 1967 [47] to describe the processing of sensory input, how it is transduced from physical stimuli into sensation, elaborated and stored in mental representations, recovered from memory and used in cognitive task performance. Rather than focusing purely on the behavioral outputs in response to reinforcement provided, cognitive psychology uses constructs that describe regularities in mental representations and methods by which those representations are processed that can be confirmed by experiments. In keeping with the focus on human information processing, Neisser proposed that people could be considered dynamic information processing systems whose mental operations can be given in computational terms (e.g. Shannon's information theory [64]). Today, cognitive psychology is a large subject area which bases theories on mental representations and processes such as implicit and explicit memory, focal attention, visuospatial processing, object and event categorization etc.

Although its focus is on information representation and processing, cognitive psychology was able to characterize a range of human capabilities and limitations that hold true over a variety of cognitive tasks. Examples of these are the working memory model (WMM) [3] and the multi-store model for human memory [2], which includes a central executive with a role in processing short term memory information from two kinds of short-term "working" memory – a visual-spatial sketchpad for spatial information and an articulatory-phonological (AP) loop for sounds, especially language – into long term storage through rehearsal.

Another well-known piece of work was Miller's 1956 [44], which applied Claude Shannon's information theory to [64] propose that the capacity limitation of the AP loop was "seven plus or minus two" or 2.5 bits of information. Because the AP loop was a key component of many information processing pathways it was claimed that its capacity would limit performance of a variety of cognitive tasks.

Computer science researchers are increasingly knowledgeable about the key points of these important older works. They are often less aware of newer, more progressive models of human cognition that might also impact their work. For example, a great deal of attention has been given to devising categorization theories that utilize information theory to describe processes of category formation and its use in cognition [38,39].

Studies of categorization give rise to two distinct theoretical traditions, supervised categorization (e.g. [48,69,74]); and unsupervised categorization, e.g. the simplicity model [55–58]. A third emerging area, relational representation in categorization, proposes theories which claim that relational properties are important in categorizing information [20,70,79]. Categorization models have been applied to many areas of psychology, including clinical and developmental psychology, for example, as a diagnostic tool for autism [19], and for traumatic brain injury [21], as well as a way of understanding cognitive development in children [18].

Other modern cognitive theories are based on information theory as well. Unitization Theory specifies information reduction in implicit memory. Experiments conducted by Unitization theorists show that through the training of a consistent sequence of events the individual events that make up this sequence eventually become part of a whole and lose their individual identity. Through unitization, information contained in a string of numbers is reduced from multiple bits of information in memory to a single bit, or "chunk" of information [30,52,53]. Theories such a Unitization Theory demonstrate that our processing of information can be altered by the sequences in which they take place. This theory may be particularly relevant to experiments where there is less control of the specific stimuli and presentation order, as is typically the case in crowdsourcing studies.

2.6 Cognition and Computer Science

Attempts to develop computer models of human performance had a deep impact on cognitive psychology. Work by David Marr [41] led to his tri-level hypothesis. This hypothesis was based on the early thinking about visual representation and was influenced in part on Shepard and Metzler's, 1971, mental rotation [68]. Marr proposed that there are three levels of description of information processing in the visual system. The 'computational theoretic level' describes the operating requirements for the system– what the system computes, what are its outputs used for, and what problem it solves. The 'algorithmic representation level' specifies the operations that take place to enable the system to solve the problem. Finally, the 'physical level' specifies the mechanisms that are responsible for the processing, e.g., which neurons process a visual stimulus and how they operate.

Applying this approach to human vision, Marr suggested that the reason for seeing places constraints on the nature of seeing. This can be considered an ecological approach to perception theory, in that it specifies that the properties of an organism's visual system are determined by the operations that vision must perform in order for that creature to survive. Finding food, escaping predation etc. place requirements on visual processing that must be operationalized algorithmically and operationalized on the physical infrastructure, i.e. the neurons.

At the algorithmic level, processing a representation can take many forms. For example, the number three can be represented in binary (11), Roman (III) or Arabic (3) numerals, by the word "three", saying "du du da", showing three fingers, using a triangle, holding three acorns, and so on. It should be obvious by looking at the different representations of three, that each representation privileges a certain algorithm, or computational process. Take, for example, the case of a lost person seeking to find their location. Different individuals may approach the problem of being lost very differently. One might navigate based on the position of the sun and shade from buildings or lampposts to determine which direction to walk. Another might look for address numbers on buildings and street signs. Yet another might look for friendly people to approach and ask for directions. In these instances the same goal can be supported by algorithmic level processes that are quite different. Each of these algorithms is constrained not only by the need to achieve the goal of the computation but also the operating characteristics of the physical neurons that perform the computation.

Marr's Tri-Level Hypothesis of vision serves as an example of how the information-processing model of mind can address the transformation between the physical world and cognitive task performance in the context of human behavior in the environment. It does this by bridging from a computational theory of the organism in its environment to the creation of representations of information and algorithms by which they can be processed. These algorithms in turn are mapped onto neural substrates for processing. Through specification of these three levels it becomes possible to generate powerful explanations for cognition in humans and in human-computer cognitive systems.

Marr's Tri-Level approach to understanding cognition was later extended to distributed cognition by Edwin Hutchins [34,35] in his theory of human interactions with external events. Hutchins' work has been a key contributor to the development of HCI work today.

2.7 Crowdsourcing Psychology Studies

In recent years, psychologists have begun to explore crowdsourced forms of data collection such as Survey Monkey, Crowd Flower and Amazon Mechanical Turk (AMT) [16]. What may be important to note is that all of these studies have taken place within the last decade. Because the use of crowdsourced experiments in psychology is quite recent, its use is still controversial and the methods used are continually being refined.

3 The Influence of Psychology on Visualization and HCI Research

This section introduces some of the ways in which psychology has been utilized in visualization and HCI research, including recent studies using crowdsourcing methods. This is done as a basic overview. The next two sections explore the advantages and limitations, as well as future directions for crowdsourcing research in these areas.

3.1 The Influence of Psychology on Visualization Research

As an applied science, visualization has benefited tremendously from the discoveries in psychology. For example, in visual design, the understanding about the ordering of some commonly used visual channels, such as color, size, shape, orientation, and symbols [28], is derived from a large collection of studies on visual search [59,76]. The phenomenon of visual multiplexing [9], which has been utilized to create effective visualization, can be ratiocinated using literary evidence in psychology, such as the multi-store model for human memory [2], Gestalt principles of organization [32], and dimensionality of the stimulus space [66]. Many recent advances in psychology are waiting to be applied in visualization, as will be discussed in the Future Directions section of this chapter.

As a way of evaluating scientific theory, visualization offers a platform by which theories of psychology can be tested and potentially disconfirmed. Fundamental questions about how people perceive complex graphical representations and reason about the information they contain may yield discoveries that are critical to both visualization and psychology. For example, how do humans adapt to constructed environments such as visualization to perform analytical tasks and decision processes? How do humans interpret, and are influenced by, uncertainty depicted in visualization? How do humans learn to interpret static patterns (e.g., a time series plot) as temporal events, and how can such skills be extended in other scenarios (e.g., visualizing a video using static imagery)?

Cognition researchers have embraced crowdsourcing platforms for a variety of empirical studies [29]. For example, there have been crowdsourcing studies on color naming [45], human visual computing [26], uncertainty encoding [5], Bayesian reasoning charts [43], and orderability judgment [11]. In each of these applications experiment design and analysis must contend with potential confounding effects in empirical data collected from these less controllable environments. It is likely that the visualization community will support this effort by contributing new visual analytics tools for observing large volumes of crowdsourced data, analyzing confounding effects and their impact, removing outliers and anomalies, and presenting analytical results. For these reasons, crowdsourcing seems to be a reasonable platform for data collection in terms of visualization research and will continue to be in the future.

3.2 Distributed Cognition in HCI Research

As discussed in Sect. 2.6, Marr's Tri-Level Hypothesis helped to give rise to a perspective on cognition that viewed it as distributed across multiple human agents, or across a human and a responsive external system. This approach to cognition proposed the use of cognitive ethnography to study human collaboration and interaction with external events by Edwin Hutchins and colleagues [31,34,35]. By viewing cognition as the interaction of representation and algorithm, Hutchins was able to develop ethnographic methods to explore cognitive processing across different kinds of cognitive systems and at different scales of observation.

In an example of this human interaction application with cognitive distribution, Hutchins compared Western and Micronesian flight navigation systems along Marr's three levels. The computational level was characterized by the self-positioning of the aircraft with respect to the task and the travel goals. While it may seem like the problem would be the same for both groups, Hutchins demonstrated key differences in the representation and algorithms employed in both groups [33]. First, in Western navigation, the ship was moving across the ocean from one location to another. The path could be drawn and calculated on a small-scale chart that represents the Earth. In the Mirconesian system, the navigator was at the center, and his position was fixed with reference to the stars and sun. There were islands he could not see which also had fixed positions with respect to the stars and sun. When the Micronesian navigator traveled in a canoe, he was aiming for a certain fixed bearing with respect to the stars and sun, by moving the Earth past him. So, while the Micronesian navigator moved the Earth past him, the Western navigator moved along the Earth.

These are very different ways of representing aspects of the environment for the purposes of navigation, and these differences continue to the hardware level. The hardware level of Marr's tri-level hypothesis includes the substrate in which the cognitive processing takes place. For the field of vision, this includes the structures of the eye and the firing of neurons in all of the systems involved in vision. For Hutchins, the hardware level includes aspects of the environment that play a role in cognition, for example, the nomograph and ruler used to calculate ship speed. Hutchins called these 'cognitive artefacts' as they perform the task of organizing functional skills into cognitive functional systems.

In parallel with the growing interest in distributed cognition in the cognitive science community, HCI research has moved beyond studies of individual task based interaction to examine groups of individuals communicating through technology [77] e.g. in computer supported cooperative work (CSCW). The psychological theory of distributed cognition has been an important component used to bridge HCI with CSCW [46].

One example of this comes from Scaife and Rogers [63]. These researchers explored how external properties of graphical representations can affect thinking and reasoning through their influence on the users' mental representations.

In another example, Mayers et al. [42] assessed user knowledge of Macintosh applications. They found that even expert users could not recall all of the menu headings. Despite their lack of recall, these users encountered no difficulties in using the menus and the application as a whole. From this, Mayers believed that users did not commit all of the applications components to memory. Rather the users relied on cues to select the correct menu. Young et al. [78], suggested that these findings challenged the well-known 'Goals, Operators, Methods, Selection rules' (GOMS; e.g., [37]) family of interaction. In Young's view the display, through cueing the user, played a more central role in controlling interaction with the graphical user interface than did the user's memory.

We find that work in psychology and HCI can be quite complimentary. Working from Mayers' findings in HCI can lead us to seek further explanations by focusing on theories in psychology involving visual cues, limits in memory stores, attentional saliency, and categorical efficiency in reducing information. While promising, these approaches of bridging HCI and Psychology work have not been sufficiently utilized. We discuss this in our Future Directions section, with an emphasis on crowdsourcing approaches.

4 Advantages and Disadvantages of Using Crowdsourcing in Psychology

This section takes a psychological perspective in exploring some of the advantages and disadvantages of crowdsourcing platforms for research. These include self-selection, response bias, representativeness of the population, and the reliability of crowdsourced experiments. We address responses to these threats in our Future Directions section by proposing an information theoretical approach to cognition with application to crowdsourcing studies.

Given the similarities between the two disciplines, the advantages and disadvantages of crowdsourced data for HCI and psychology may be similar. From the psychology literature, Crump et al. [16] suggests that one of the major concerns about laboratory experiments is the challenge of obtaining quick, large and reliable samples. As well, the lack of diversity of the population obtained threatens the external validity of the study results. This view is supported by other psychologists, for example, Reips [60] suggests that the advantages of using crowdsourcing over laboratory experiments is the ability to generate a large sample and diverse demographic, whilst the disadvantages are the loss of control and self-selection in subject recruitment. Other concerns about laboratory studies, include the pygmalion effect, where the experimenter's expectations lead to higher performance by the participant [6,62]; low power due to unavailability of students wishing to participate [12,25]; and demand characteristics [49,61], where participants, often students of the same subject area, believe that the experiment demands a certain outcome. In contrast, crowdsourcing data gathering provides access to a more diverse participant pool, with lower costs [29,65]. Other advantages and disadvantages are discussed below.

4.1 Self-selection and Completion Rates

Shawver et al. [65] suggested that the completion rates and how the experiments are completed may play a role in the success and accuracy of findings. Their findings demonstrated a higher completion rate for participants in face-to-face (laboratory) settings when compared to online settings. However, the higher completion rate in the face-to-face setting did not result in better data. The greater accuracy of the online data could be due to the self-selection nature of the online platform, with individuals dropping out of the survey based on some internal cue about the quality of their own responses and without pressure to remain in the study until the end. These pressures may exist in laboratory settings and may affect the quality of the data, with less accurate data generated as a result.

4.2 Representativeness of the Data

Using AMT or other online platforms to gather data does not automatically ensure that the participants or their responses will be representative of a diverse population. Researchers can take measures to strengthen the diversity of the data pool by using a filter or clustering procedure [15]. However, simply being open to the general public means that crowdsourcing has the potential to attract a more diverse population in comparison to university-based laboratory studies that draw from a student population.

4.3 Reliability of Crowdsourced Experiments

Concerns about lack of control in studies conducted using crowdsourcing can be ameliorated in the same way that laboratory studies are, through replication in other studies and by other researchers. The test-retest validity of crowdsourcing found high test-retest reliability when using an AMT population for psychometric tests [7]. This was also the case for Gosling et al. [27] who found good reliability in questionnaire surveys conducted using an internet population. In addition to this, Paolacci et al. [50] replicated several one-shot decision-making experiments on AMT. These studies used well-researched tasks such as the Asian disease problem test for framing effects [73], the Linda problem test for the conjunction fallacy [72], the Physician problem test of outcome bias [4] and the Prisoner's dilemma game [13]. However, these experiments do all involve the participant making a single decision about a question, so these were not cognitively demanding.

Despite the fact that AMT has been demonstrated as useful and reliable for simple, and cognitively non-demanding tasks, very little work had been conducted in the psychology community to evaluate the usefulness of crowdsourcing for more complex cognitively demanding experiments.

Many cognitive psychology experiments require accurate (typically millisecond) measurement of subject reaction times. This level of accuracy is common in studies of attention. These studies may also require multi-trial designs and complex instructions, making them challenging for crowdsourcing methods. Crump et al. [16] replicated several of these cognitively demanding reaction time studies using crowdsourcing: the Stroop task-switching experiment [40]; the Flanker task [22]; the Simon task [14]; the Posner cuing tasks [54]; and the category learning task [67] with good results in a series of short 5 min studies. To our knowledge no replications have been conducted for longer scale cognitive psychology experiments that are typical for laboratory studies.

5 Future Directions for Improving Visualization and HCI Crowdsourced Experiments

We will conclude this chapter by suggesting how recent information processing theories and models from psychology could support more effective use of crowdsourcing for visualization and HCI research.

While classical theories from cognitive psychology, such as the multi-store model for human memory [2], Gestalt principles of organization [32], and dimensionality of the stimulus space [66] are a good starting point for design and analysis of HCI laboratory studies, they are not well suited for crowdsourcing methods.

When using crowdsourced methods experimenters should be aware that they have less control over what is being presented to the participant than in laboratory studies. More recent modeling approaches to understanding human cognition may prove more useful in guiding the design and analysis of these studies. One example of this is the Relative Judgment Model of categorization (RJM [70]). This model specifies how the order of stimuli presented to the participant will affect the decision-making process and the accuracy of the subject responses. Through the use of RJM it may be possible to factor out the effects of variability of stimulus presentation encountered in crowdsourcing studies, reducing their ability to obscure the effects of interest.

Other recent information processing models could prove useful for HCI work. Mayers et al. [42] explored the information processing nature of cognition. Theories of unitization and contextual locking [52,53] can predict how user procedures can become unitized in memory as a conceptual "chunk" and as a perceptuo-motor procedural "script". A string of procedures – e.g. 'press start' then 'press menu', then 'press select application' – initially require multiple discrete decisions, taking up several bits of information stored in working memory. According to unitization theory these bits of information can be reduced to a single bit of information after learning. Through procedural learning, the number of bits in working memory can reduce to a single bit of information capturing the entire procedure. As Mayers et al. [42] suggest, an explicit (i.e. conscious) memory of each of these steps is not needed once the sequence of actions has been learned.

Models of chunking and procedural learning could play an important role in interpreting crowdsourced experiments. As with RJM, these models may be able to be used in crowdsourcing to both study their phenomena of interest and to factor out these learning effects, thus enabling analysis of other variables of interest.

For studies conducted in relatively contaminated and uncontrolled environments, computational and mathematical models of human cognition can be used to model complex data and to factor out known effects, producing a clean dataset for subsequent statistical and modeling analysis.

6 Conclusion

This chapter has sought to (1) introduce the broad nature of psychology; (2) offer some examples of how psychology has been applied to visualization and HCI; (3) explain some of the advantages of using crowdsourced experiments, as identified through the psychology literature; and (4) to offer some new approaches from contemporary information theories of psychology that can be applied to crowdsourced experiments.

As crowdsourced research grows in importance we must continue to advance new methods for designing, validating, and analyzing results from complex experiments. We believe that the advantages of crowdsourcing will make this effort worthwhile.

Acknowledgment. We would like to express gratitude to Dagstuhl for facilitating the seminar (titled, 'Evaluation in the Crowd: Crowdsourcing and Human-Centred Experiments'), which has allowed this collaboration to develop.

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