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Structured Sensemaking of Videographic Information within Dataphoric Space

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By

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Abstract

Attempts to create a structured sensemaking model have proven difficult. Much of the research today has evolved into a cacophony of conceptual models. Many of these sensemaking models have been proposed but not tested. Using structural equations, a unified model of sensemaking was developed and tested. This structured sensemaking model contains five sensemaking constructs: chaos, anchoring, articulation, retrospection, and identity. This model was tested using data collected from 224 educationally focused YouTube videos. The confirmatory factor model developed for this research has a measured Comparative Fit Index of 0.979, a measured Standardized Root Mean Square Residual of 0.078, and a measured Akaike's Information Criterion of 182.892. The associated structural model has a measured Comparative Fit Index of 0.991, a measured Standardized Root Mean Square Residual of 0.047, and a measured Akaike's Information Criterion of 131.680. This theory of structured sensemaking supports a) the unification of five sensemaking constructs b) a structured sensemaking framework c) the integration of information theory and d) a reusable sensemaking method. This structured sensemaking framework is the first of its kind.

Keywords

structured sensemaking, sensemaking, theory of structured sensemaking, human-computer interaction, individual sensemaking, information theory, entropy, perception, content development, education, videos, video content, chaos, anchoring, articulation, identity, retrospection, confirmatory factor analysis, structural equation modeling

Declaration

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

Michael J. Pritchard

Chapter 1 – Introduction

This research is organized in the following way: Introduction, Literature Review, Theory, Methodology, Data Analysis, and Discussion. The introduction will state the problem and the significance of the research. It will also describe what to expect in the coming chapters of this research. The literature review will encompass a broad body of sensemaking research. It will categorize this body of research into research themes and it will locate where this research falls within those thematic research areas. The theory section will provide a clear understanding of the major perspectives. It will be a focused review of the different sensemaking theories as well as the juxtaposition of information theory within the overall framework. The methods section will connect the research theories into a complete methodological picture. It will outlay the data sources, technologies and statistical methods. The data analysis section will be a deep dive into the various models employed within this research: two factor models and the final structural model. In addition, model tuning and metrics will be discussed. The research will conclude with a discussion. The discussion will review the significance of the findings, strengths as well as limitations.

Overview of Sensemaking

Humans categorize knowledge they encounter. Categorization of knowledge, in turn, is used to create situational awareness; this is sensemaking (Klein, Moon, and Hoffman, 2006). In an effort to simplify complex topics, humans codify observable knowledge into symbols to help describe and quantify the incoming chaos of sensory information. The letters on this paper represent such a construct. These symbols form words, words form sentences, and sentences form manuscripts. Over time, humans encoded in these manuscripts ever more complicated thoughts (Eco, 1976). They “articulated” their thoughts and “anchored” their ideas. From mathematics to music, humans observed and created information from the chaos of information. Over time humans began to transmit their ideas and thoughts over greater distances. After all, does an idea exists if no one else is around to contemplate it? Existentially, yes, the idea still exists; however, to us humans we need validation. How can we be sure that our very thoughts truly exist in the first place? We require connection with others to validate our senses. Humans get around this issue through sharing. It is no surprise that as technology evolved, so did our need to share information.

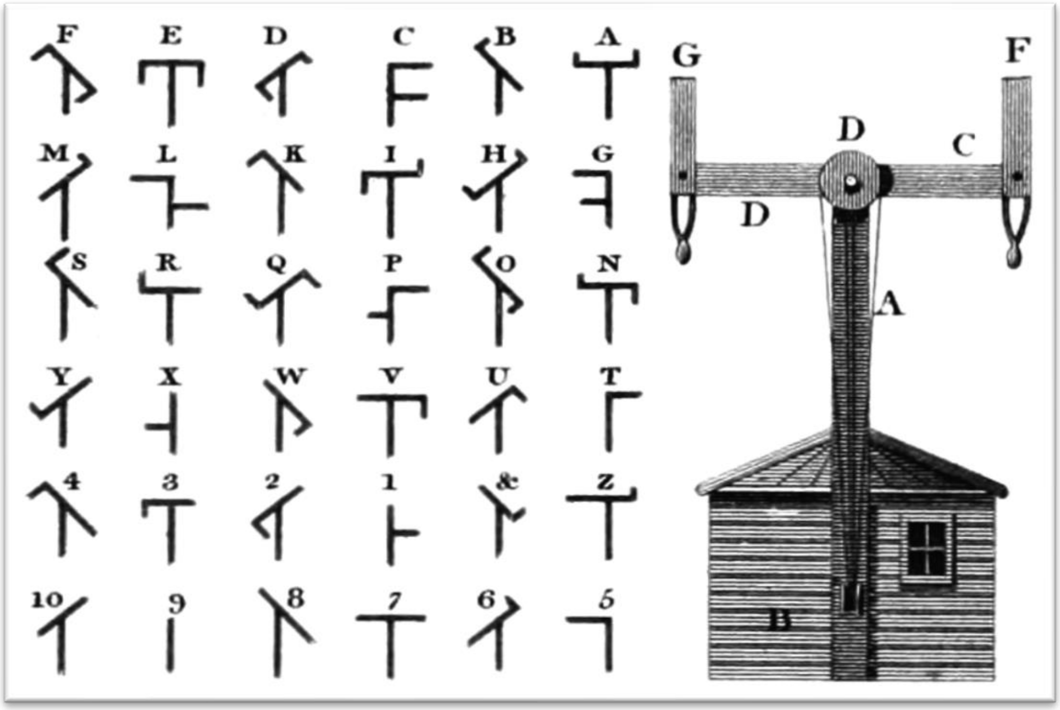


Figure 1. Chappe’s Semaphore (Holzmann, 1994)

In 1616, Franz Kessler published a booklet in which an optical communications framework could be built with the aid of telescopes (Holzmann, 1994). The optical telegraph would not be fully realized until 1791, when Claude Chappe built a robust optically-based communication system in 1791. It was a crude system by today’s standard. It required each communication node on the network to have a codebook and a telescope. It also required a synchronized clock system along each node. In addition, Chappe’s system required line of sight tower placement. The receiver looked through a telescope to decipher the code being transmitted (usually placed atop a tower) (Standage, 1998). The tower’s mechanism would be positioned to create a symbol. The tower’s symbol generating mechanism was called a semaphore (see Figure 1. Chappe’s Semaphore). These semaphores, when positioned in certain configurations, provides signification and meaning to the receiver. The abstract symbols devised by Chappe were linked to letters. As the semaphore changed shape, it would then be codified to have different “meaning”. Chappe's semaphoric communication scheme required the transmitter to "give a sense" of the message such that the receiver could "make sense" of the incoming data. While our communication systems have changed much over the past 200 years, the fundamentals of sensemaking have not.

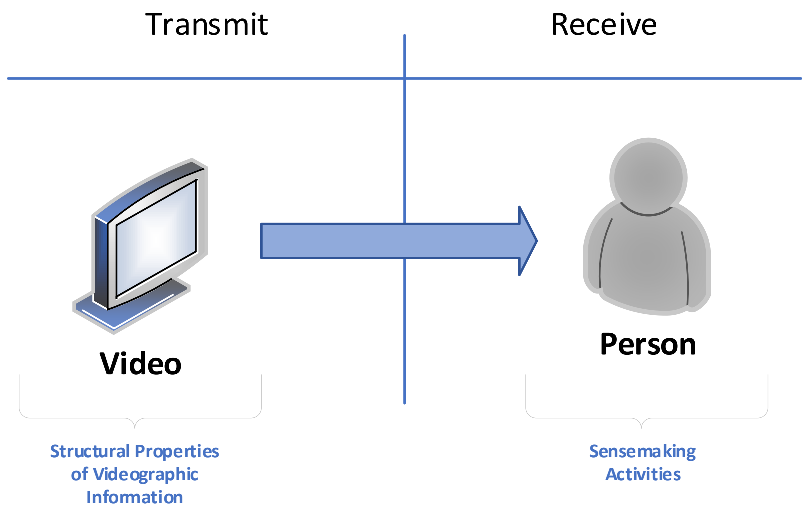


Figure 2. Observation Space

Sensemaking is a social activity. It is a process by which people give meaning to their joint experiences. Much like Chappe's Semaphore, the observation space of this research involves the transmission of information. Except, in this case, the information is a bit more contemporary. The observation space is the human reception of videographic content over the internet (See Figure 2. Observation Space). As humans, we receive a lot of incoming sensory information. This data is transmitted to us constantly via various sensory mechanisms (e.g., sight, sound, smell, touch, and taste). Making sense of this incoming data starts with Chaos. Chaos is the process by which humans work to sift out important signals from a noisy environment (Weick, Sutcliffee and Obstfeld, 2005). Once a human detects a signal, they work to make sense of what they are receiving. In an effort to do so, a human engages in Retrospection. This retrospection occurs through a sharing of information via discussions and remarks among interdependent actors. Incoming sensory information is "talked" and "symbolically encoded" into existence via conversations and texts that are preserved in a social structure (Weick, Sutcliffe and Obstfeld, 2005; Blum et al., 2014; Takazawa, 2010). Humans retrospect to *compare* notes. For example, sensemaking can easily be described in the following:

- During breakfast, a child and her parents are eating together before the school bus arrives. The father reaches into the breadbasket to give his daughter more bread for breakfast. The daughter, being the youngest at the table, does not have the codified experiences of her parents. However, she spots something odd about the bread. After all, she has eaten bread

> before. “Dad, does this food have mold on it?” She senses green spots on the bread. These visual “anchors” provide clues. But because she was not sure, she collaborated with her father to confirm.

The daughter undertakes two simultaneous tasks before asking her question. First, she is being bombarded by her biological senses, she is managing entropy in real-time, she is managing the “chaos”. From this sensory chaos, she spots something out of the ordinary - an “anchor” of information - green spots on her bread. She ponders and then has to give sense to the situation. She “articulates” to her father her concern. The concern can either be validated or dismissed. This communicative back and forth is called “retrospection”. For example, the father could say, “I am not sure, what does your mother think?” This is an expansion of the retrospection process. For retrospection to go smoothly, the collaborative process requires that the content in question has anchors and is articulable (articulators). Anchors serve to ground concepts (for example, a mental model of mold on food) and articulators work to unify taxonomies (e.g., green spots on food is mold? Or something else?). Lastly, the individual determines to “identify” with the data they are receiving. This identification is a value-based identity (i.e., is this moldy food important for me to be aware of?) (Jiménez, García, and de Ayala, 2016). Creating an identity with important data is useful for human survival, it reinforces a continued need to be aware of the information. After all, it would be detrimental to her health if the daughter in this example continues to misidentify moldy bread.

In addition to sensemaking, there is sensegiving (Gioia and Chittipeddi, 1991). Sensegiving is the data transmission of information to the human receiver. It describes what is imparted into the content itself. It is the structural components of the information to be transmitted. Within this research Anchoring, Articulation and Chaos are collectively related to the “structural properties of information” – and more specifically – videographic information. Anchors are "key indicators" within a data stream. Creating anchors within the data stream is based on the Data-Frame Theory. These are sensory data points that help the sensemaker unpack the data frame they are experiencing (Brown et al., 2008; An, Kulm and Ma, 2008; Klein, Phillips, Rall and Peluso, 2007; Beer, 1998). Articulation is a process by which tacit knowledge is made more explicit through various mechanisms and activities (Russell et al., 1993; Stigliani and Ravasi, 2012). In addition, it is the categorization of streaming data, “...in ways that predispose people to find common ground”

(Weick, Sutcliffe and Obstfeld, 2005). Chaos within this research is an entropically bound construct (i.e., information entropy of the videographic information) (Weaver, 1949). The Chaos construct relies on the Theory of Dataphoric Space (Pritchard and Noteboom, 2018). The data within a dataphoric ecosystem has a measurable entropic expression and is useful within the framework of this research. This research is focused at the individual level; an individual's sensemaking activity with the data being received.

This research is significant for a number of reasons. There are multiple competing sensemaking paradigms (Ntuen, 2006; Namvar et al., 2018). At an individual sensemaking level, this research helps to solidify the competing paradigms into a single sensemaking model. This research supports a) the integrated sensemaking framework amongst these five sensemaking constructs b) a structured sensemaking framework c) the integration of information theory and d) a reusable sensemaking method. This structured sensemaking framework is the first of its kind.

Chapter 2 – Literature Review

In the Data-Frame Theory, data is fitted to a cognitive frame of reference. This fitting of data to one's frame of reference is very similar to the concept of an "ergonomics of information", a subfield within human-computer interaction. Ergonomics can best be described as the study of fitting technology, devices, or even processes to the human body (Dul et al., 2012). In the case of data, the “ergonomics of information” refers to the fitting of data to the individual (See Figure 3. Ergonomics of Information). The term is first referenced by William Thomas Singleton, in a keynote address to the IEE Conference on ‘Display’ at Loughborough University in 1971 (Singleton, 1971). At the time, Singleton was a professor of applied psychology and the head of the Applied Psychology Department at Aston University from 1967 to 1982 (Singleton, 2018). In contrasting ergonomics and the ergonomics of information, Singleton described it in the following way, “It could be argued that ergonomics as a technology distinct from the human sciences must incorporate these wider factors but it seems justifiable, for the present purpose, to use the term ergonomics to signify an approach to information presentation…” (Singleton, 1971). Some years later, a team of researchers continued to detail out the need for an "…ergonomics of information and knowledge structures" (Storrs, Rivers, and Canter, 1984).

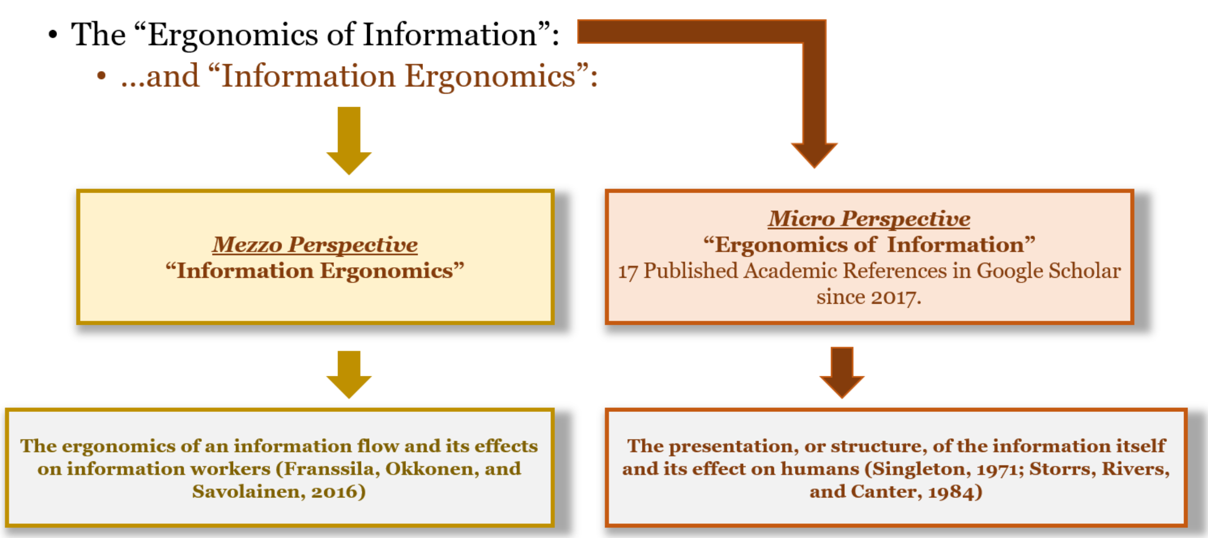


Figure 3. Ergonomics of Information

By their very definitions, sensemaking and the ergonomics of information are indistinguishable from each other (Russell et al., 1993; Namvar et al., 2018). Each describes the fitting of data to the individual, and each describes the fitting of data to an organization. Within the academic literature, sensemaking has overtaken the ergonomics of information. In 2017, 17 academic references were found using the term "ergonomics of information". Conversely, over 8,958 academic references were found using the term "sensemaking" over the same time period. Which bodes well for the body of research as a whole. Given this information, the literature review is focused on sensemaking. Keyword usage in this literature review was strict in keyword pairings. Keywords were strictly wrapped using “and" operations as opposed to a more relaxed "or" search operation among keywords.

Sensemaking is comprised of seven distinct research areas: Enacted/Ecological/Crisis, Process, Organizational/Strategic, Information Theory, Participatory/Collaborative, Individual and Leadership (See Table 1. Sensemaking Research Since 2017). The Enacted/Ecological/Crisis portion of the research is the largest by far. It accounts for almost 63% of the literature being published since 2017. The Enacted/Ecological/Crisis area is motivated by action-oriented response within an actor/theater relationship (with an emphasis on emergencies, disasters and crises). It can be thought of as a systemic view of sensemaking that combines both the mobilization of individual actors, the mobilization of organizations to remediate situational issues or threats (Seidel et al., 2018; Introna, 2018; Gephart Jr and Ganzin, 2018; Benaben, Sakurai, and Tapia, 2019). The Process portion of sensemaking research is the second largest. From 2017 to present it accounted for over 16% of academic sensemaking references. Process-based sensemaking as a discipline is focused on the methodological aspects of sensemaking as it pertains to either individuals or organizations. This portion of the academic literature is moving towards a more complete theory of sensemaking (De Luca Picion, 2018; Richter and Arndt, 2018; Bajwa, Waseem, and Akbar, 2018). The Organizational/Strategic portion of sensemaking accounts for over 11% of the research literature. The Organizational/Strategic area takes sensemaking research into an ecosystem perspective. This perspective treats the organization as a socially constructed colony. In some instances, the organization is viewed as an organism that reacts to its surrounding environment much like a human would (Helms Mills and Mills, 2017; Stigliani and Elsbach, 2018; Jalonen, Schildt, and Vaara, 2018). The Participatory/Collaborative portion of sensemaking account for just over 3% of the literature published since 2017. It is an up and coming portion of the research base due to an ever-increasing connectivity between social media systems. The Participatory/Collaborative slice of sensemaking gives us insight into how interdependent actors identify and retrospect with content through sharing and discussions (Zhao et al., 2018; Siegel and Schraagen, 2017; Tao and Tombros, 2017).

Sensemaking Area	Since 2017	Percent	Keywords Used
Individual Sensemaking & Information Theory	2	0.02%	"Individual Sensemaking" + "Information Theory"
Leadership	88	0.98%	"Leadership Sensemaking", "Sensemaking Leadership"
Information Theory	146	1.63%	"Sensemaking" + "Information Theory"
Individual	254	2.84%	"Individual Sensemaking"
Participatory/Collaborative	307	3.43%	"Participatory Sensemaking", "Collaborative Sensemaking"
Organizational/Strategic	1060	11.83%	"Organizational Sensemaking", "Strategic Sensemaking"
Process	1470	16.41%	"Sensemaking Process"
Enacted/Ecological/Crisis	5631	62.86%	"Enacted Sensemaking", "Ecological Sensemaking", "Disaster Sensemaking", "Sensemaking" + "Crisis"
	8958		

Table 1. Sensemaking Research Since 2017

Sensemaking, as it pertains to the individual, is a small portion of the sensemaking research base. It accounts for just under 3% of the research. This portion of the research branches into two distinct subgroups: anthropological and psychological. The psychological portion of the research base crosses over into human-computer interactions more so than the others. It is an intimate behavioral view that explores the audio, video and tactile feedback a human receives (Lowe and Rod, 2018; Peña et al., 2019). The anthropological perspective can be described as being culturally driven. It aims to understand better how culture impacts human sensemaking (Aguinis and Glavas, 2017; Ivanova-Gongne and Torkkeli, 2018). The sixth sensemaking area on this list is Information Theory. Information Theory is a very small portion of the sensemaking literature. It accounts for just over 1% of academic references since 2017. Information Theory brings Information Entropy into the scope of sensemaking. It is highly quantitative, and like quantum mechanics, highly probabilistic (Kodagoda, 2017; Holman, 2018; Miller and Licklider, 1949). The usage of Information Theory is a major component of this research area. Lastly, there is Leadership. Leadership is the smallest research area within sensemaking. Leadership as a sensemaking process helps to determine what daily activities are undertaken to lead in the most effective manner possible. Leadership crosses over into the anthropological Individual as well as the Organizational/Strategic areas of sensemaking (Faris and Abdalla, 2018; Lehmann-Willenbrock, 2018).

The literature is expansive; however, gaps exist within the sensemaking discipline. First, there remains disagreement on what sensemaking really entails (Namvar, et al., 2018). Consequently, research constructs are not clearly delineated within the research (Odden, 2019). Second, information entropy predates all of the earliest academic discussions regarding sensemaking by many decades (Shannon's communication work in 1948, Miller and Licklider's work in 1950 versus Weick in 1966 and Singleton in 1971). Which is quite surprising considering that Claude Shannon's communication research is very much at the heart of sensemaking. His theory of information entropy revolutionized communication (Rogers and Valente, 2017). Yet, it has largely been absent in modern sensemaking literature. The popularity of sensemaking is undeniable; yet, the juxtaposition of individual sensemaking and information theory is sparse. Since 2017, using the terms "individual sensemaking" and "information theory" only accounted for two master level theses (Matic, 2017; Ficova and Belloni, 2017).

This research builds out the necessary integration of these two theories: that of sensemaking and that of information theory. In understanding the nature of data, knowledge and information, there is much to be learned (Boisot and Canals, 2004; Dervin, 1998). Inforomation entropy is a useful measurement mechanism (Holman, 2018; Pritchard and Noteboom, 2018). Additional information structures have been tested in the context of sensemaking. For example, in a smaller sample size, it was determined that music aids in the acquiring of math skills (An, Kulm and Ma, 2008). In another study, novice ‘sensemakers’ try to make sense of unfamiliar visualizations using different visual cues (Lee et al., 2016). Further complicating the matter of sensemaking in this research space is the number of competing theoretical frameworks (Klein, Phillips, Rall, and Peluso, 2007; Namvar et al., 2018; McNamara, 2015). This has provided researchers with new observable research constructs as it relates to information systems research (Weinberg & Thomas, 2018; Oh, Eom and Rao, 2012; Landry and Guzdial, 2008). These new avenues not only explore human hyper-connectivity but also how we as individuals sense data from an information-theoretic perspective. This research looks to expand on the analysis of videographic information that is more generalizable, reusable and includes information entropy.

Sensemaking: Not Particularly Tidy

In 2005, a presentation was given to the 10th International Command and Control Research and Technology Symposium. It characterized the many issues of sensemaking. A notable quote found within the presentation describes the issue well, "...it would sure be nice if we had some clear idea what it was we were trying to do first." -Michael Boorda, Admiral USN & Joint Chief (Deceased) (Leedom, 2005). The presentation illustrated many common sensemaking themes: sensing data, collaboration, knowledge cues, situational frames, and knowledge identification. One could say it broadly outlines a sensemaking agenda for the military. However, in all, it did not present any data. It was hard to determine if any models were of any use.

In the following year, a flurry of military-focused sensemaking papers were released. One paper entitled “Cognitive constructs and the sensemaking process” (Ntuen, 2006) came not from the military circles, but from academia. It describes a model but like the others, it contains no hypothesis, nor any data to substantiate the proposed framework. In 2009, Leedom published the “Anticipatory Understanding of Adversary Intent: A Signature-Based Knowledge System” (Leedom and Eggleston, 2009). Leedom and Eggleston present a research ontology aimed at understanding adversarial intent. It is focused on solving military issues related to pre-battle, battle and post-battle knowledge sensing, meaning creation, and decision structure. This research presents a framework but suffers the same fate as its predecessors. It does not present either qualitative, or quantitative, evidence of its actual usefulness.

Fast forward ten years and sensemaking research is still largely being applied in a conceptual sense. Recently, a paper published by Aguinis and Glavas continues this notable conceptualization trend, "Our conceptual framework for understanding how individuals make sense...relies on sensemaking as an underlying and unifying mechanism” (Aguinis and Glavas, 2019). This paper reads more like an emergent research manuscript. No hypotheses are established, no data is presented.

This conceptulationzation is noted in another recently published case study by Schildt, Mantere, and Cornelissen (Schildt, Mantere, and Cornelissen, 2019). This case study does not provide any hypothesis. It is not clear what the authors are trying to prove (even conceptually it is not clear). This paper is self-acknowledged to suffer from what Weick has described, sensemaking "is not particular tidy, which means that attempts to portray it may also sprawl" (Weick, 2001; Schildt, Mantere, and Cornelissen, 2019).

Simply stated, the research space is in flux and full of opportunity. Many papers are conceptual and offer little proof of their conjectures. This research looks to move sensemaking research from unstructured to structured. This research contains a clear sensemaking model, clear hypotheses and clear quantitative testing procedures. This research will determine the efficacy of the structured sensemaking framework using principled research methods and rigorous statistical analyses.

Chapter 3 – Theory

Sensemaking Theory

This research combines the theories of sensemaking with that of information theory. To better understand what sensemaking is, and is not, it is best to review the history of sensemaking through the history of psychology (Everson, 1991). Sensemaking is foundationally based in psychology, "...psychology has the most to offer in the way of a sense-making framework for understanding human behavior." (Lindgren and Byrne, 1961). Psychology has a long history. In 387 BC, Plato suggested that the brain was the basis of mental processes (Robinson, 1995). Not to be outdone, Aristotle decided the complete opposite and suggested that the heart was the basis of all mental processes. Moving forward many millennia, it was not until the 1800s that psychology became a discipline unto itself. Ernst Heinrich Weber developed a theory of perception known as “Just Noticeable Difference" (JND), it is famously known as Weber's Law (Weber, 1996). Weber's Law was published in 1834, and is the earliest manifestation of a theory of signal detection. Weber's Law stipulates that where I is the original intensity (e.g., crowded restaurant), ΔI has to be increased by that much more such that a signal can be detected from the original intensity (e.g., shouting in a crowded restaurant). Where k is an increment constant threshold. Weber's Law is a good baseline approximation of many sensemaking phenomena (See Figure 4. Weber’s Law).

“Change in stimulus”

$$\frac{\Delta I}{I} = k \rightarrow$$

“Percent of change that results in detection of difference in stimulus.”

“stimulus”

Figure 4. Weber's Law

In 1883, the first psychological laboratory in the United States was established at Johns Hopkins University (Murray and Rowe, 1979). The development of the program (and school as a whole) were largely rooted in the European nondenominational tradition (Fuchs, Evans, and Green, 2007). In the 1880s, Herman Ebbinghaus developed theories on perception, learning, and memory that are still in use today (Ebbinghaus, 2013). In 1886, Sigmund Freud opened up a mental therapy shop in Vienna (Freud and Strachey, 2001). While controversial, Sigmund contributed greatly to the field of psychology. Equally compelling is Freud's daughter Anna. In the 1900s she contributed considerable research material to childhood learning processes and perception (Freud, 1974). Rounding out the 1900s, is Margaret Floy Washburn. In a time, where animal research primarily focused on rats, Dr. Washburn's work developed one of the most comprehensive works on differential animal cognition (Pillsbury, 1940). Her original works in animal cognition are still very relevant to this day.

In 'The Animal Mind', Washburn detailed the problems in sensemaking without using the term 'sensemaking' (Washburn, 1917). Yet, the word 'sense' shows up 149 times in her comparative analysis of animals. One has to look no further to understand - that Dr. Washburn - understood the concept of sensemaking:

> "...our inferences are made on the basis of words or of actions, they are all necessarily made on the hypothesis that human minds are built on the same pattern, that what a given word or action would mean for my mind, this it means also for my neighbor’s mind. If this hypothesis be uncertain when applied to our fellow human beings, it fails us utterly when we turn to the lower animals. If my neighbor's mind is a mystery to me, how great is the mystery which looks out of the eyes of a dog, and how unsoluble the problem presented by the mind of an invertebrate animal…
>
> ...for example, of an "angry" wasp. Anger, in our own experience, is largely composed of sensations of quickened heart beat, of altered breathing, of muscular tension, of increase blood pressure in the head and face....the wasp does not breathe through lungs, it wears its skeleton on the outside...What is anger like in the wasp's consciousness?"
>
> - Washburn, Margaret Floy (Washburn, 1917)

Her sensemaking insight is extremely compelling and no less relevant today. She makes an important distinction regarding not only the human perceptual understanding of words between humans as a collective but also the misguided projection of narratives upon other phenomena. The use of language has become even more complicated between humans when viewing Dr. Washburn's insights from a contemporary perspective. In addition, as per Washburn’s own writings, she is actively engaging in “articulation” she is articulating the concept of “anger”.

Unlike the moldy food example, she cannot engage in “retrospection” with the Wasp. The wasp and human cannot create a shared identity of “anger”.

The first official view of sensemaking appears in 1961, within a psychology paper introducing the study of human behavior, "...is the belief that of all the sciences, psychology has the most to offer in the way of a sense-making framework for understanding human behavior." (Lindgren and Byrne, 1961). Lindgren and Byrne's book is an introductory textbook in psychology. In 1966, the lineage breaks off from the individual and encompasses an organizational perspective of psychology (Katz and Kahn, 1966). This shifted the cognitive focus towards organizations. In 1969, Karl Weick published "The Social Psychology of Organizing". It was a different take on organizational psychology in that Weick proposed a framework that focused on the sensemaking process itself (Weick, 1969). Sensemaking, or sense-making, is the process by which people give meaning to their collective experiences. It has been defined as "the ongoing retrospective development of plausible images that rationalize what people are doing" (Weick, Sutcliffe, & Obstfeld, 2005). Weick intended to encourage a shift away from the traditional focus of organizational theorists on decision-making and towards the processes that constitute the meaning of the decisions that are enacted in behavior. While Weick’s early premise was organizationally focused, his views adjusted over time to also include the sensemaking processes of the individual (Weick, Sutcliffe, & Obstfeld, 2005). In essence, bringing the organizational sensemaking research back to its individualistic roots.

Five Theories, Two Perspectives

There are five distinct sensemaking models (See Figure 5. Combined Sensemaking Perspectives). The first describes sensemaking as, "…a methodology disciplining the cacophony of diversity and complexity without homogenizing it." (Dervin, 1998). The second considers sensemaking as, "...the process of searching for a representation and encoding data in that representation to answer task-specific questions...” (Russell et al., 1993). The third suggests sensemaking as, "…the ongoing retrospective development of plausible images that rationalize what people are doing..." (Weick, Sutcliffe, & Obstfeld, 2005). The fourth describes sensemaking as, "...the processes of organizing using the technology of language - processes of labeling and categorizing for instance - to identify, regularize and routinize memories into plausible explanations." (Brown, Stacey, and Nandhakumar, 2008). Finally, the fifth framework postulates, "...that elements are explained when they are fitted into a structure that links them to other elements." (Klein et al., 2007). The first two frameworks comprise a more information-centric perspective to sensemaking. The next two make up a major portion of the traditional sensemaking research literature (i.e., a psychosocial perspective of sensemaking). The fifth framework is the newest model of sensemaking. It is known formally as Data-Frame Theory. Data-Frame Theory is rooted in the psychosocial perspective of sensemaking and was built with the individual's cognition as its core component.

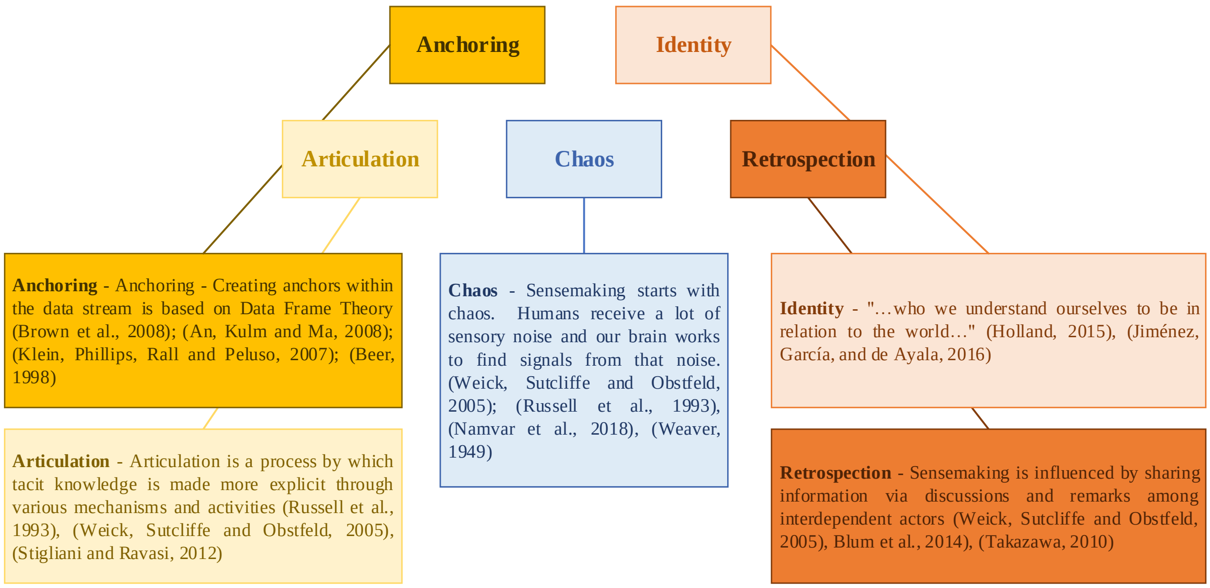


Figure 5. Combined Sensemaking Perspectives

Dervin’s model describes sensemaking as a verb-driven system "... emphasizing diversity, complexity and sense-making potentials" (Dervin, 1998). Dervin's approach is focused on human-computer interaction between a knowledge worker and a knowledge management system. She describes how queries to a knowledge management system are optimal when the queries themselves are action-focused versus noun-focused.

Russell’s model of sensemaking has a design science orientation through a type of cost-based information ecology - that is, a knowledge worker develops a cost function as it relates to the worker’s information-seeking behavior. When trying to make sense of a problem, the knowledge worker is challenged with getting information manually or aided by a computer. Regardless of the perceived intuitiveness of a computer-based approach, humans engage in foraging-like cost behavior when seeking information (Russell et al., 1993).

Weick’s model has been used to describe the sensemaking activities of organizational actors. Organizational actors have to manage organizational flux, "...an almost infinite stream of events and inputs that surround any organizational actor." (Weick, Sutcliffe, and Obstfeld, 2005). Weick further describes that sensemaking requires collaboration and retrospection. This component of Weick's model relates to how sense is developed through retrospection with one's thoughts and then discussing these thoughts with others.

The fourth perspective is also based on the psychosocial model and is an expansion of Weick’s perspective. In this case, the researchers expand into social interactions where organizational actors employ impression management in a collaborative setting. Brown's research revealed that while organizational actors are motivated towards a general agreement of the facts, they are motivated to create their own personal interpretations of what has occurred (Brown, Stacey, and Nandhakumar, 2008).

The fifth and final perspective is a micro-focused cognitive model that asserts, "...that the way people make sense of situations is shaped by cognitive frames that are internal images of external reality." (Klein et al., 2007). The research draws heavily on Barlett, Goffman, Minsky, Neisser, and Piaget (Barlett, 1932; Goffman, 1974; Minsky, 1975; Neisser, 1976; Piaget, 1952). This model of sensemaking makes use of "just in time” mental models. They suggest that people do not form comprehensive mental models and instead rely on constructed fragments of "local cause-effect connections". As such, efforts to increase information within a decision support system negatively impact decision-makers. They challenge the data, information, knowledge paradigm related to information processing. Instead, they advocate for an ecological approach to data construction.

Based on the five distinct models discussed, sensemaking models are categorized as being either sociotechnical or psychosocial. Both Dervin and Russell view sensemaking from a knowledge worker perspective. This view of sensemaking was developed from a sociotechnical perspective. Weick and Brown view sensemaking from an organizational actor perspective and view sensemaking as a psychosocial framework. While psychological in nature, Klien's work is aligned with Weick. Dervin and Russell do not reference Weick related literature. In addition, Dervin and Russell are not referenced to each other. Klien and Brown are both referenced to Weick. Klein and Russell are related in that they both suggest an ecological approach be incorporated into data construction. This referencing suggests that the sociotechnical, and psychosocial, models of sensemaking are competing paradigms (Namvar et al., 2018).

Information Theory

The history of information theory begins with a history of statistics. In 1564, the concepts of probability were developed via games of chance. The Italian polymath, Gerolama Cordano, made significant contributions to probability theory (Ore, 2017). However, Cordano was a troubled scientist; he had a gambling problem. This gambling problem lead him to be in constant debt. He was compelled through his gambling problem to become a better gambler. Due to his gambling habit, he created the foundation of modern probability theory (Bernstein and Bernstein, 1996). While conceptually relevant, his theories of probability were considered rudimentary and did not hold up to scientific scrutiny. Cardona could not "disassociate the unscientific concept of luck from the mathematical concept of chance. He identifies luck with some supernatural force..." (Gorroochurn, 2012). It would be another one hundred years before a more rigorous theory of probability would be realized. In 1654, in their consideration of the "problem of points" Blaise Pascal and Pierre de Fermat formally defined the concept of conditional probability. The "problem of points" had been known for many years, but never solved. The problem is summarized in the following way: given that a person A has won *m* games and person B has won *n* games, what is the probability that A will win the series? This is not an easy solution as the possible paths of play are not equally likely. In addition, the probabilities change due to the plays that have already occurred in the past (Grinstead and Snell, 2012). This highlighted the "dependence" of events as it relates to statistical outcomes. This was documented in greater detail via "The Doctrine of Chances" in 1718 by Abraham De Moivre (De Moivre, 1756). Years later, Thomas Bayes would be credited for fully clarifying conditional probability. In 1763, an essay was published posthumously after Bayes' death. In it, Bayes "considered a new kind of inverse probability problem requiring the use of conditional probability." (Grinstead and Snell, 2012). Today his most famous contribution is known as Bayes' Theorem (See Figure 6. Bayes' Theorem)

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

Figure 6. Bayes' Theorem

This type of conditional probability had remarkable generalizability. Prior to Bayes, probability theory was largely relegated to games of chance and matters of insurance. For example, using Bayes' theorem, if cancer is related to age, then it is possible to accurately determine the probability that a person has cancer-based on their age. Of course, the statistical analysis is only as good as the model under evaluation. For example, a predictive correlation can be rigorously made regarding the relationship between pirates and global warming (Fairhurst and Atherton, 2014). An observational accounting of the phenomenon is required before a probabilistic assessment can be taken seriously. This kind of probabilistic determinism would later influence the creation of Markov Chains (See Figure 7. Markov Chain Example). Markov Chains were created in 1907 by Andrey Markov (Basharin, Langville, and Naumov, 2004). Markov Chains are a set of "states". These states can represent the probability of a system (e.g., the weather). As a state transitions to a new state of being (e.g., cold weather to warm weather) its probabilities also change (Grinstead and Snell, 2012). These transition probabilities are maintained in a transition matrix (i.e., a matrix that contains the probabilities of the various transition states).

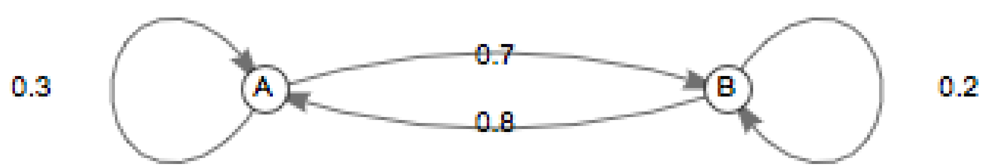
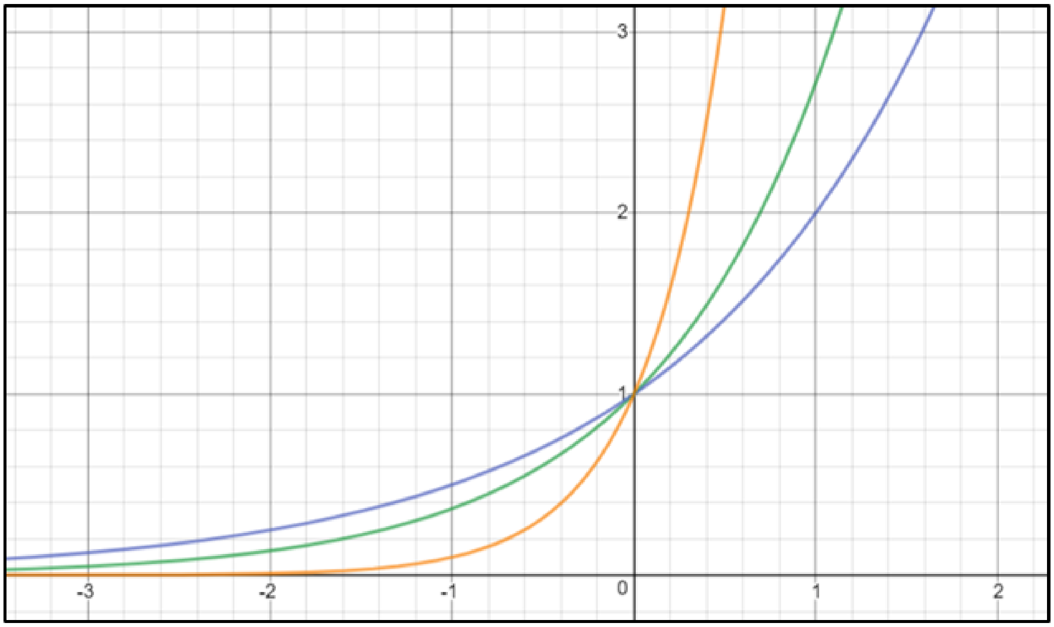


Figure 7. Markov Chain Example

Shortly after devising this statistical mechanism, Markov applied this framework to that of the human language (Markov, 2006).

In 1948, Claude Shannon combined the concept of a Markov chain with that of thermodynamics to create what is known as Information Entropy (Shannon, 1948). Information entropy is a measure of data communication bits and its measurement depends on the base of the logarithm. Commonly, the base of the logarithm is 2, 2.718 (e = Euler's Number), or 10. Euler's number is most commonly used as it approximates the limit of growth in regards to natural systems (Maor and King, 1994). A log of base 2 would represent a system of slow growth and a log base 10 would represent a system of faster growth (See Figure 8. Log Base Curve Examples).



$$x = log_e y\text{(green)},\ x = log_2 y\text{(blue)},\ x = log_{10} y\text{(orange)}$$

Figure 8. Log Base Curve Examples

Information entropy provides for an absolute limit on the shortest possible average length of encoded data to be produced by a data transmitter. If the entropy of the transmitter is less than that of the communication medium, then the odds increase that the information can be detected by a receiver. In addition, Information Entropy is a probabilistic function. For example, if the measured entropy of a system is zero, then we as human observers of the system are certain of its outcome. Notice the distinction being made. Information Entropy is not an attribute of the system, but an estimated measure of what we as an observer can know about a system. However, we can only qualify this when the contents of the source (or events) are known. For example, let us imagine a hypothetical box completely devoid of information. Next, if we introduce a single bit of data into the middle of the box - say the letter 'A' - then its entropy can now be evaluated. Its entropy value would be equal to zero. If we introduced another letter into the box resulting in 'AB', then the entropy value would increase to 1. If we add yet another letter resulting in 'ABC', then the entropy value would further increase to 1.58 (See Figure 9. Information Entropy Box).

The log base ensures that growth is limited (it is not a linear growth pattern). Let us repeat the experiment, but in the next version three letters are replaced with the exact same letters 'AAA'.

The resulting entropy value drops back down to zero. The two redundant symbols beyond the first symbol do not tell us anything that we do not already know that we did not already receive from the first symbol. Entropy can inform this research in regards to how much 'variation' there is within the content. Lastly, the meaning of the data being transmitted does not matter in the definition of entropy. Entropy is the probability of observing a specific event. Consequently, information entropy encapsulates only the probability of what is observed, not the meaning of the actual data in transit to the receiver.

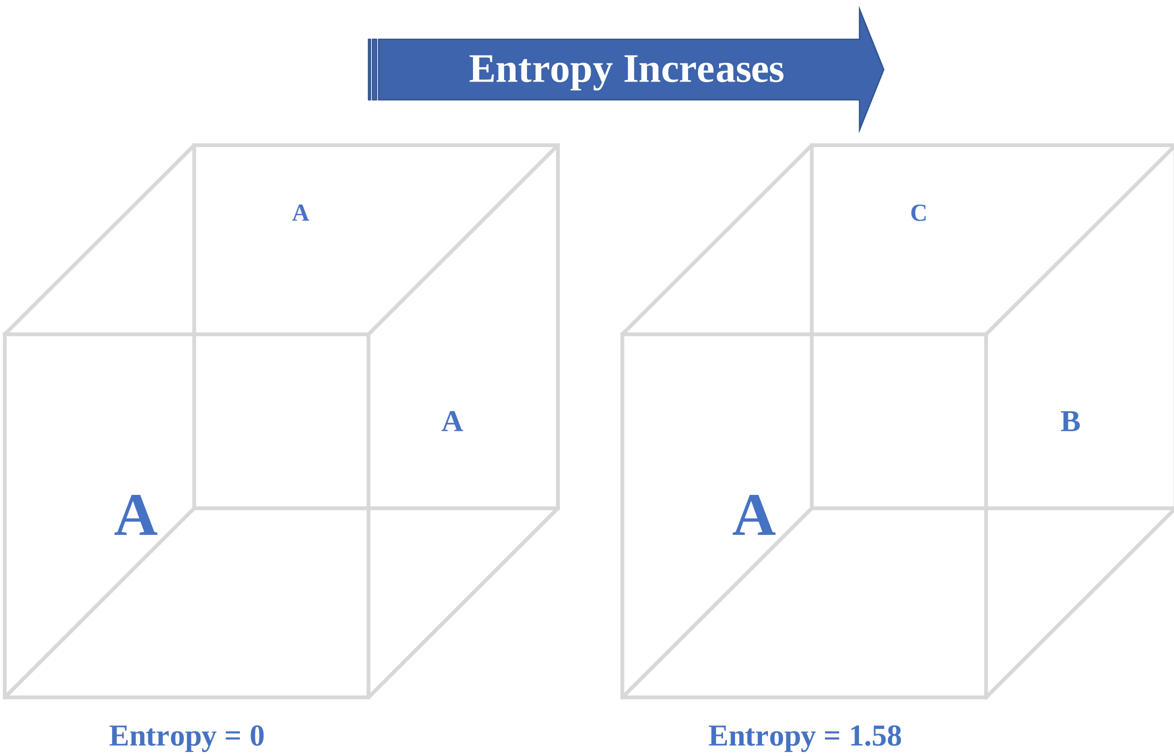


Figure 9. Information Entropy Box

This research meakes use of both perspectives of sensemaking (i.e., sociotechnical and psychosocial) and the information-theoretic framework known as Information Entropy. This research applies the entropic calculations to the visual imagery to determine the level of variance a person observes from within the videographic content. The sensemaking constructs as described in the prior section when glued together become the structured sensemaking model.

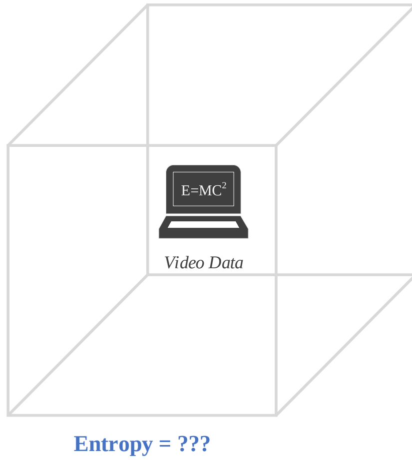


Figure 10. Entropy of Video

Structural Properties of Information

This research is leveraging videos and sample images taken from those videos. Image samples are broken down into their component structures via image vectorization techniques (Jimenez and Navalon, 1982). This yields imagery variance and color variance using the standard deviation of entropy as a measure of the variance (See Figure 10. Entropy of Video). Each video is evaluated manually to determine if it contains any cards, music, models or mathematical objects. The default sound decibel is captured from YouTube metrics at the time of evaluation. Lastly, the research captures the content length of the video, words per minute of the video speaker, as well as keywords used by the video. The details and operationalizing of variables will be discussed in a subsequent section (See Chapter 4, section Operationalizing the Research Model).

Observation Space & Information Content

The observation space is composed of a data transmitter (i.e., the video) and a data receiver (i.e., the human). The structural properties of the information discussed above are related to video content. The videographic content is educational in nature. The content being captured varies across popular educational channels to lesser-known education channels and university lectures. Hundreds of videos will be captured leading to the creation of over 1,000 video image samples. 26 educational topics will be chosen from across 120 different video channels. The related sensemaking activity of each video will also be captured (i.e., what the person does after viewing the content).

Research Questions & Goals

The goal is to positively impact the way that visual information is constructed such that it maximizes its highest sensemaking potential. This research is expected to create descriptive and predictive insights regarding the sensemaking of videographic information structures. Lastly, this research will showcase the efficacy of the structural sensemaking framework.

- Is the integrated sensemaking framework amongst these five sensemaking constructs valid?
- Is the idea of a structured sensemaking framework useful and measurable?
- Can information theory be integrated into this sensemaking framework?
- What are the limits of this method? How generalizable is it?

Research Hypotheses

H1. The articulation of content has a positive effect on identity behavior

First Hypothesis - Sensemaking theory describes articulation as a process in which tacit knowledge is made more explicit through various mechanisms and activities (Russell et al., 1993; Stigliani and Elsbach, 2018). Articulation is the categorization of streaming data, "...in ways that predispose people to find common ground" (Weick, Sutfliffe, and Obstfeld, 2005). Identity describes how people associate with content that defines their cultural belief system. It is, "…a place for constructing identity, where multiple communities are generated...and make other means of communication possible through favorites or video groupings." (Jiménez, García, and de Ayala, 2016). The articulation of information is captured via the content length, words per minute and keyword usage. These are attributes of the content itself. Identity is operationalized via likes, views, and subscribers. The first hypothesis seeks to understand the relationship between the articulation of content and the identification with said content.

H2. The articulation of content has a positive effect on retrospection behavior

The second Hypothesis - Sensemaking theory also describes what is called retrospection. Retrospection is a behavior that is defined by the sharing of information via discussions and remarks among interdependent actors. Retrospections are both self-reflective and collaborative. Incoming sensory information is "talked" and "symbolically encoded" into existence via conversations and texts that are preserved in social structures (Blum et al., 2014; Takazawa, 2010; Weick, Sutfliffe, and Obstfeld, 2005). The second hypothesis seeks to understand the relationship between the articulation of information content and the behavior of retrospection.

H3. Retrospection behavior has a positive effect on identity formation

Third Hypothesis – This hypothesis will test the relationship between identity behavior and retrospection behavior. The data variables for these two sensemaking constructs are downstream dimensional attributes of the video (i.e., what a human does after viewing video content). While sensemaking theories are somewhat vague, the structured theory of sensemaking can be formalized via the captured performance data within the social computing platform. This data resides in the form of comments associated with the video and externally linked discussion also related to the video content. Similar to product development strategies, these narrative retrospections may strengthen the formation of identity-related behaviors.

H4. Anchoring of content has a positive effect on identity formation

Fourth Hypothesis - This hypothesis will test the relationship between the usage of anchors within the content and if there is statistical significance with identity formation. The latent Anchor construct is comprised of models, music, math, and cards. Each video was manually evaluated to determine the presence of each anchor within the video content. The concept of anchoring is based on Data-Frame Theory (Klein et al., 2007).

H5. Anchoring of content has a positive effect on retrospection behavior

Fifth Hypothesis - This hypothesis represents the usage of anchors and their relationship to retrospection behavior. Based on sensemaking theory - specifically, Data-Frame Theory - the usage of anchors should have an impact on retrospective behavior. In this case, it is believed that visual anchors serve as a way for individuals to index a topic via an anchor type. In addition, some anchors may elicit stronger statistical significance (i.e., usage of models versus a mathematical equation).

H6. Chaos has a positive effect on the anchoring of content

Sixth Hypothesis - The latent chaos construct is defined via entropy, imagery variance (as measured by the standard deviation of image entropy across the sampled images across the video),

video loudness (as measured by vidIQ) and total color variation. In sensemaking theory - specifically, Weick's theory of sensemaking - sensemaking begins with chaos (Weick's 2005 reference here). The chaos construct is illustrated via entropy and imagery. It is believed to be pertinent to anchor usage. For example, higher model usage will create more image variation and color variation throughout a video. This should illustrate a positive relationship between these two constructs.

H7. Chaos has a positive effect on the articulation of content

Seventh Hypothesis - Articulation, as described in the first hypothesis, is the content length, words per minute and keyword usage. Entropy should have significance to the articulation of content. For example, an increase in distinct symbol usage relates to an increase in entropy (Pritchard and Noteboom, 2018). There may be a positive relationship between these two constructs.

H8. Chaos has no effect on identity formation

Eight Hypothesis - This hypothesis represents a relational test between chaos and identity. Content must exist before identity formation can occur. Even if the individual has never heard of the content (e.g., heard it from a friend), identity formation can occur prior to the individual physically seeing the content, but regardless of seeing it, or not seeing it, the content exists prior to the formation of an identity. Based on the placement of identity formation it is believed that no statistical relationship exists between chaos and identity formation.

H9. Chaos has no effect on retrospection behavior

Ninth Hypothesis - What holds true for identity should also hold true for retrospection behavior. Retrospection activities cannot occur before the content is created. Based on the placement of retrospective behavior there is the possibility that no statistical relationship exists between chaos and retrospection behavior.

H10. Articulation of content has a positive relationship on the anchoring of content

The tenth Hypothesis - In the final test, the relationship between anchoring and articulation is tested. Anchoring and articulation are part of content creation and occur before retrospection behavior and identity formation (i.e., content must be created before those two constructs can be engaged). Given this placement of anchoring and articulation within the sensemaking framework, there is a possible relationship between these two constructs.

Each of the hypotheses listed above is operationalized by 18 variables (indicators in SEM terminology). Each sensemaking construct is further refined by multiple variables (See Figure 11. Proposed Causal Model). These variables are defined in the next section (Chapter 4, Research Methodology).

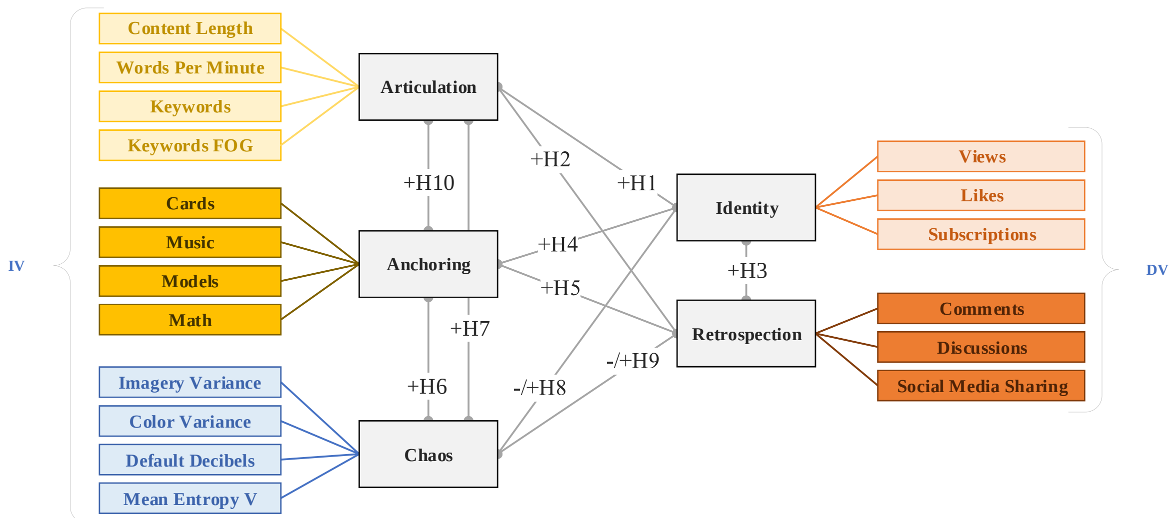


Figure 11. Proposed Causal Model

Chapter 4 – Research Methodology

Data will be collected from the five distinct constructs (See Figure 12. Research Method & Constructs). The underlying factor data will be captured and stored in a SQL Server database. This allows for advanced data analysis, data visualization, scaling, ordering, and application of descriptive statistics. The video imagery will be vectorized using the Python programming language. The vectorized image data will also be loaded into the SQL Server database.

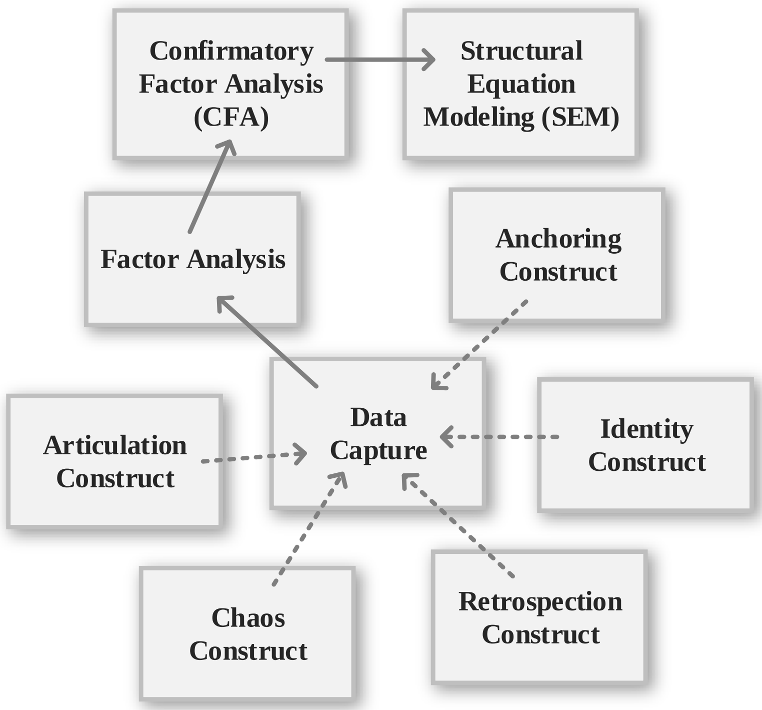


Figure 12. Research Method & Constructs

The captured sound data (words per minute and default decibels) is captured at the time the video is sampled. Sensemaking factors (i.e., factors related to the Identity and Retrospection construct) will also be captured at the time the video is sampled. Advanced social media metrics will be captured via a platform called vidIQ (Purcariu, 2015). Once all the data is compiled, all the factors will be analyzed primarily via Confirmatory Factor Analysis and Structural Equation Modeling. In addition, it is rare for a draft factor model to fully survive without adjustment through to the structural model – that is to say - model tuning will be required. This may involve latent construct adjustments through trial and error as well as indicator adjustments through item parceling (Hair et al., 2010; Hall, Snell, and Foust, 1999).

Structural Equation Modeling

Structural equation modeling (SEM) is a form of causal modeling (Lomax and Schumacker, 2004). SEM is an ensemble method that uses a diverse set of mathematical models and statistical methods: confirmatory factor analysis, confirmatory composite analysis, path analysis, partial least squares path modeling, and latent growth modeling (Kline, 2011). This combination of techniques allows for the statistical testing of one or more multiple independent variables (IVs) to that of one or more dependent variables (DVs). In addition, the IVs and DVs can be factors or measured variables (Ullman and Bentler, 2003).

The use of SEM is widely used within the social sciences (Ullman and Bentler, 2003). The nomenclature of SEM is tied to 'path diagrams'. These path diagrams are fundamental to SEM as they allow the researcher to clearly articulate the hypothesized variable relationships within the model (See Figure 13. Example of Path Diagram). Measured variables are called observed variables. Indicators are called manifest variables. Each factor has two or more indicators. These are the latent variables. Relationships between variables are represented by black lines.

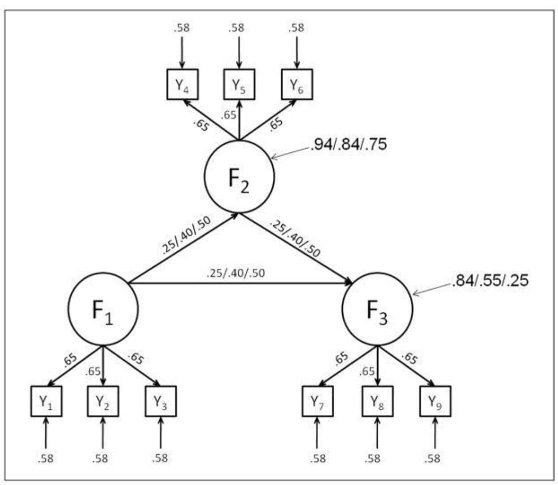


Figure 13. Example of Path Diagram (Wolf et al., 2013)

SEM analyses are part measurement model and part structural model. The measurement model is defined as the part of the model that relates the measured variables to the factors (Ullman and Bentler, 2003). The structural portion of SEM is the hypothesized relationship among the various constructs (e.g., as depicted in the Path Diagram). SEM follows a four-stage process: model specification, model estimation, model evaluation, and model modification. Additionally, SEM generally requires between 5 and 10 samples per variable under analysis (Wolf et al., 2013; Bentler and Chou, 1987). This puts the research sample size requirement between 90 and 180 (18 variables times 5, or 18 variables times 10). In summary, this research has 5 latent constructs with 18 total variables. Given the sample size requirement, it was decided to exceed the high side of the requirement with a research sample size of 224. Both CFA and SEM analyses will be managed via SPSS AMOS software that is specially designed for this type of research.

Operationalizing the Research Model

The research model contains 18 variables (See Figure 14. Research Constructs & Variables). The Articulation construct is operationalized by four variables: content length, words per minute, keywords and the Gunning Fog Index of the keyword (FOG). Content Length is a measure of video length. It is the total run time of the video as measured in seconds. Words Per Minute is a metric that tracks the average words per minute spoken within the video. A higher number represents a faster pace of speech found within the video. Keywords is a metric that captures the number of keywords associated with the video. It is a total raw number of keywords tagged to the video. The actual keywords associated with the video were captured. These keywords were then assessed for readability using the Gunning Fog Index (FOG). FOG is a readability test for English writing. It was developed 1952 and is still commonly used to confirm the readability of text (Gunning, 1969; Skierkowski et al., 2018).

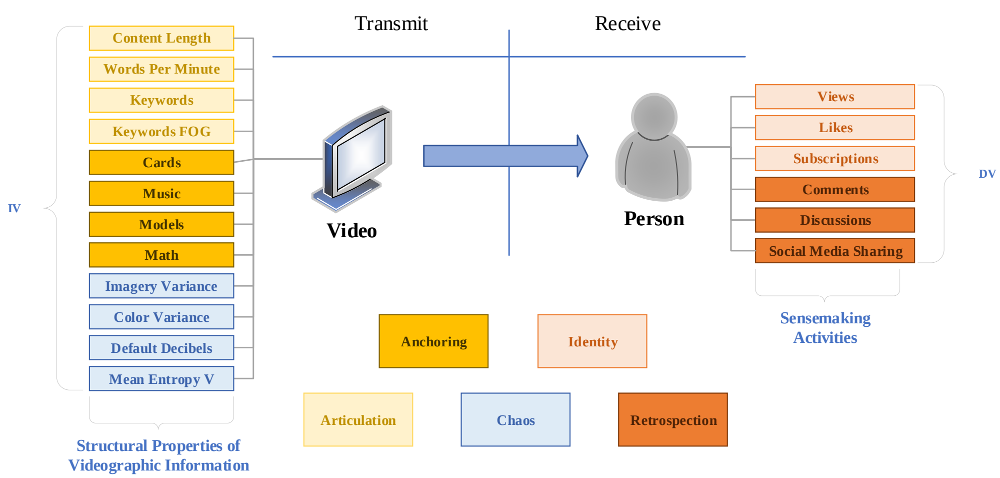


Figure 14. Research Constructs & Variables

Anchoring is operationalized by four variables: Cards, Music, Models, and Math. If Music is present within the video, then the video is marked as having music. Opening music does not count towards this metric. This metric only matters if music is found preceding the opening. If Models are present within the video, then the video is marked as containing models. Models must be conceptual diagrams, graphs, mockups, or representations that conceptually mimic physical phenomenon. If Math is present within the video, then the video is marked as having math. For this to get marked, the mathematical topic must be explored beyond simply displaying an equation. The equation must be discussed or represented more comprehensively as a topic within the video. Cards are interactive panels that slide in and out of a video while it is playing. They encourage additional interaction by the sensemaker.

Chaos is operationalized via four variables: Imagery Variance, Color Variance, Default Decibels, and Mean Entropy V. Imagery variance is the standard deviation of the Mean Entropy (i.e., the average entropy of the vectorized image data calculated via the six image samples per video). Mean Entropy V is the average entropy of the vectorized image data. It is a mean of the mean entropy values of each sample image taken from each video (i.e., six image samples per video). The entropy value is able to describe the level of uniformity within the image. The lower the entropy value the more uniform the image. Statistically speaking, Shannon Entropy is also how much we know about what we are seeing. Higher values indicate a more complex scenery (i.e., higher complexity, leads to more uncertainty). A lower entropy value in this context also indicates more certainty about what we are seeing. The Color Variance is a mathematically derived data point within the dataset. It is described as the summated standard deviation of the percent extracted red, percent extracted green and percent extracted blue of the vectorized image component for a given red, green or blue component. In addition, the Color Variance is summated across six image samples from within each video sample. The Default Decibels is a YouTube metric. It is a normalization value for the default sound noise level as determined by YouTube. It is measured in decibels. If the value is negative then the video stays at a negative decibel level. The video will open by default less loud. If the decibel is positive the video will be renormalized such that the sound source is adjusted to the loudness target value as much as possible within a range where the sound wave peaks do not clip. A higher number means a higher default opening sound level.

Retrospection is operationalized via three variables: Comments, Discussions and Social Media Sharing. Comments are a measure of the number of comments as it relates to the video. Many researchers have focused on using YouTube comments for what many call "Collaborative

Sensemaking" (Blum et al., 2014; Takazawa, 2010). Discussions, specifically, is a measure of more dialogue. This is primarily a measure of advanced dialogue on Reddit beyond the dialogue found within the comments section of the YouTube video. It is a total of all Reddit activities: upvotes, comments, and posts. Social Media Sharing is a categorical metric that represents if the video is not being shared, being shared by Facebook, being shared by twitter, or being shared by both.

Lastly, the Identity construct is operationalized via three variables: Likes, Views and Subscribers (Holland, 2015). Likes are a discrete metric. YouTube Likes are determined via the number of likes observed at the time the video was observed. This is a metric generated by YouTube. Views is another discrete metric. Views are determined by the number of times a user visits a video. This is a non-distinct number and captures the total number of times a video is viewed regardless of the user. Lastly, a YouTube subscriber is someone who has chosen to “follow” a channel so that they can stay updated on the latest happenings on that channel. Users are notified when the latest videos have been added to the channel. A subscriber is usually a fan who watches, comments and shares videos with others. The Subscribes is a total count of subscribers on that channel.

Video Collection and Data Capture

224 video data samples were captured from YouTube. The video collection is topically driven and educationally based. In all, 32 scientific topics were captured. Each topic has seven videos of varying characteristics. For example, a video search was conducted on educational topics related to the “Fermi Paradox.” Videos were then reviewed to verify their educational focus. Next, construct indicators of well-known to lesser-known samples were then captured from within the specific topic. This process was repeated across 32 different educationally related topics (i.e., 32 topics times 7 video samples per educational topic equals 224 samples). According to Hair (Hair et al., 2010), the sample size is double the minimum required (i.e., 10 to 1 indicator ratio). Social media metrics were captured via vidIQ (Purcariu, 2015). The data collected are discrete, numerical and ordinal. Each of the variables was then range rescaled (range: 0 - 100). Table 2 presents the information of the data features captured (see next page for Table 2).

Construct Group	Variable Name	Variable Description	Value Range	Data Type
Articulation	Content Length	This is a measure of the video length. It is the total run time of the video as measured in seconds.	30 ~ 6984 | mean = 1526	Discrete, Ratio
	Words Per Minute	This metric tracks the average words per minute spoken within the video. A higher number represents a faster pace of speech found within the video.	0.0 ~ 223.0 | mean = 146.1	Continuous, Ratio
	Keywords	This metric captures the number of keywords associated with the video. It is a total raw number of keywords tagged to the video.	0 ~ 62 | mean = 16	Discrete, Ratio
	Keywords FOG	This metric refers to the Gunning Fog Index (FOG). FOG is a readability test for English writing and is commonly used to confirm the readability of text.	0 ~ 40.4 | mean = 16.1	Continuous, Ratio
Anchoring	Music	If Music is present within the video, then the video is marked as having music. This metric only matters if music is found preceding the opening.	• 0 = No Music • 1 = Music	Binary, Nominal, Categorical
	Models	Models must be conceptual diagrams, graphs, mockups, or representations that conceptually mimic physical phenomenon.	• 0 = No Models • 1 = Models	Binary, Nominal, Categorical
	Math	The mathematical topic must be explored beyond simply displaying an equation. The equation must be discussed or represented more comprehensively within the video.	• 0 = No Math • 1 = Math	Binary, Nominal, Categorical
	Cards	Cards are interactive panels that slide in and out of a video while it is playing. They are visual anchors that encourage additional interaction by the sensemaker.	• 0 = No Cards • 1 = Cards	Binary, Nominal, Categorical
Chaos	Imagery Variance	This is the standard deviation of the Mean Entropy (i.e., the average entropy of the vectorized image data calculated via the six image samples per video).	0.37 ~ 5.30 | mean = 3.46	Continuous, Ratio
	Mean Entropy V	This is the average entropy of the vectorized image data. It is a mean of the mean entropy values of each sample image taken from each video (i.e., six image samples per video).	0.30 ~ 5.30 | mean = 3.46	Continuous, Ratio
	Color Variance	The Color Variance is the summated standard deviation of the percent extracted red, percent extracted green and percent extracted blue of the vectorized image across six image samples taken from the video.	1 ~ 145 | mean = 53	Discrete, Ratio
	Default Decibels	A value for default sound noise level as determined by YouTube. It is measured in decibels, if the value is negative then the video stays at a negative decibel level. The video will open by default less loud.	-25.30 ~ 4.80 | mean = -2.62	Continuous, Interval
Retrospection	Comments	This is a measure of the number of comments as it relates to the video.	0 ~ 28883 | mean = 2058	Discrete, Ratio
	Discussions	This is primarily a measure of advanced dialogue on Reddit. It is a total of all Reddit activities: upvotes, comments, and posts.	0 ~ 33052 | mean = 750	Discrete, Ratio
	Social Media Sharing	This is a categorical metric that represents if the video is not being shared, being shared by Facebook, being shared by twitter, or being shared by both.	• 0 = No Social Media Sharing • 1 = Sharing on Facebook • 2 = Sharing on Twitter • 3 = Sharing on Facebook and Twitter	Nominal, Categorical
Identity	Likes	A discrete metric, YouTube Likes are determined via the number of likes observed at the time the video was observed. This is a metric generated by YouTube.	0 ~ 298000 | mean = 20786	Discrete, Ratio
	Views	A discrete metric, views are determined by the number of times a user visits a video. This is a non-distinct number and captures the total number of times a video is viewed regardless of the user.	38 ~ 14631307 | mean = 977932	Discrete, Ratio
	Subscribers	This is the number of subscribers associated with a YouTube video. A subscriber is someone who has chosen to “follow” a channel for regular updates.	0 ~ 16000000 | mean = 1579854	Discrete, Ratio

Table 2. Summary of Video Data

The data features captured are as follows:

- Content Length – Total seconds of the video as measured by YouTube.
- Words Per Minute – Average words per minute spoken via vidIQ metric service
- Keywords – Number of Keywords used by the video
- Keywords FOG – Keyword readability score as measured by Gunning Fog Index
- Views – Views as measured by YouTube
- Likes – Likes as measured by YouTube
- Subscribers – Number of subscribers as measured by YouTube
- Comments – Number of comments as measured by YouTube
- Discussions –Reddit discussions (vidIQ)
- Social Media Sharing – Category: Facebook, Twitter or both (vidIQ)
- Math – The presence of mathematical equations within the video
- Music – The presence of music within the video
- Model – The presence of models within the video
- Cards – The presence of YouTube cards within the video
- Image Variance – The standard deviation of entropy across image samples from each video
- Color Variance – The overall color variance across image samples from each video
- Mean Entropy V – The average entropy across image samples from each video
- Default Decibels – The default decibels as measured by YouTube

The data features are operationalized in the following way:

- Articulation Features
  - Content Length | Words Per Minute | Keywords | Keywords FOG
- Identity Features
  - Views | Likes | Subscribers
- Retrospection Features
  - Comments | Discussion | Social Media Sharing
- Anchoring Features
  - Math | Music | Model | Cards
- Chaos Features
  - Image Variance | Color Variance | Mean Entropy V | Default Decibels

Chapter 5 - Data Analysis & Results

Three models were reviewed: Model A, Model B, and Model C. Model A is termed the Initial CFA Model. It is used to determine both the initial strength of the latent constructs as well as the indicators within the constructs. In addition, Model A will be used to determine what indicators should be removed based on low regression weights. Low regression weights are an indicator of no statistical significance and indicate low predictive usefulness in the final structural model. Model B is termed the Tuned CFA Model. This model is used to evaluate the effectiveness of indicator removal. Namely, indicators of low statistical significance (regressions weights within a 10% approximation of zero). In addition, model fit statistics will be evaluated to determine overall model convergence and model significance via 18 model metrics (see Table 3. Model Metrics).

Model Evaluation - Fit Statistics	**Model A: Initial CFA**	**Model B: Tuned CFA**	**Model C: Tuned SEM**
chi-square ($X^{2)}$	314.58	108.892	69.680
Degrees of Freedom (df)	125	54	47
Normed chi-square (<2.0-5.0)	2.517	2.017	1.483
p-Value (<0.05)	0.0001	0.0001	0.017
Normed Fit Index (NFI) (>0.95)	0.876	0.959	0.973
Tucker-Lewis Index (TLI) (>0.95)	0.903	0.969	0.987
Relative Fit Index (RFI) (>0.95)	0.848	0.940	0.962
Comparative Fit Index (CFI) (>0.95)	0.920	0.979	0.991
Goodness-of-Fit Index (GFI) (>0.95)	0.868	0.935	0.955
Standardized Root Mean Squared Residual (SRMR) (<0.08)	0.092	0.078	0.047
Root Mean Square Error of Approximation (RMSEA) (<0.05 – 0.08)	0.082	0.068	0.047
Akaike's Information Criterion (AIC)	406.580	182.892	131.680
Model Analysis →	Not Good	Good	Excellent

Table 3. Model Metrics

Lastly, Model B will be used to determine if any borderline indicators can be statistically boosted via item parceling (Hall, Snell, and Foust, 1999; Bandalos and Finney, 2001). If the model metrics of fit indicate a high-quality model then the factor loadings can be taken into account. Latent construct factor loadings will be evaluated to determine cross correlational strength amongst latent constructs. The third and final model - Model C - is termed the Tuned SEM Model. This model 'structures' the latent constructs into a process model. The final structural model will be presented according to the observation space; video properties in relation to user behavior.

Model A Analysis

The initial CFA model has a chi-square of 314.580, 125 degrees of freedom and a normed chi-square of 2.517 (See Figure 15. Model A: Initial CFA Model and Table 4. Model A Reliability). These values are considered good. In addition, the model *p*-value is measured well below the 0.05 threshold. However, overall measures of fit illustrate a model that is not fit. The Normed Fit Index, Tucker-Lewis Index, Comparative Fit Index, and Goodness-of-Fit Index are all below the 0.95 threshold. Average Variance Extracted (AVE) also indicates that two of the five latent constructs are reliable (e.g., retrospection and identity).

Model A: Average Variance Extracted (AVE)					
Indicators	artic	retro	ident	chaos	ancho
ts	0.280				
wp	-0.070				
kc	-1.04				
kc_fog	-0.700				
di		0.800			
co		0.980			
sm		0.540			
li			1.000		
vu			0.960		
sb			0.750		
stdev_entrp				0.790	
tcv				0.740	
entrp				0.390	
ld				0.030	
math					0.010
music					0.680
model					0.470
cards					0.520
AVE > 0.50	41.307	**63.07%**	**82.80%**	33.12%	23.85%
CR > 0.60	49.96%	**82.93%**	**93.44%**	58.07%	48.09%

Table 4. Model A Reliability

Model tuning is advised, given the initial CFA model fit metrics and measured values of extracted variance (AVE). Per CFA tuning guidelines, in an attempt to tune the model, regression weights that are near zero will be removed first (Hair et al., 2010).

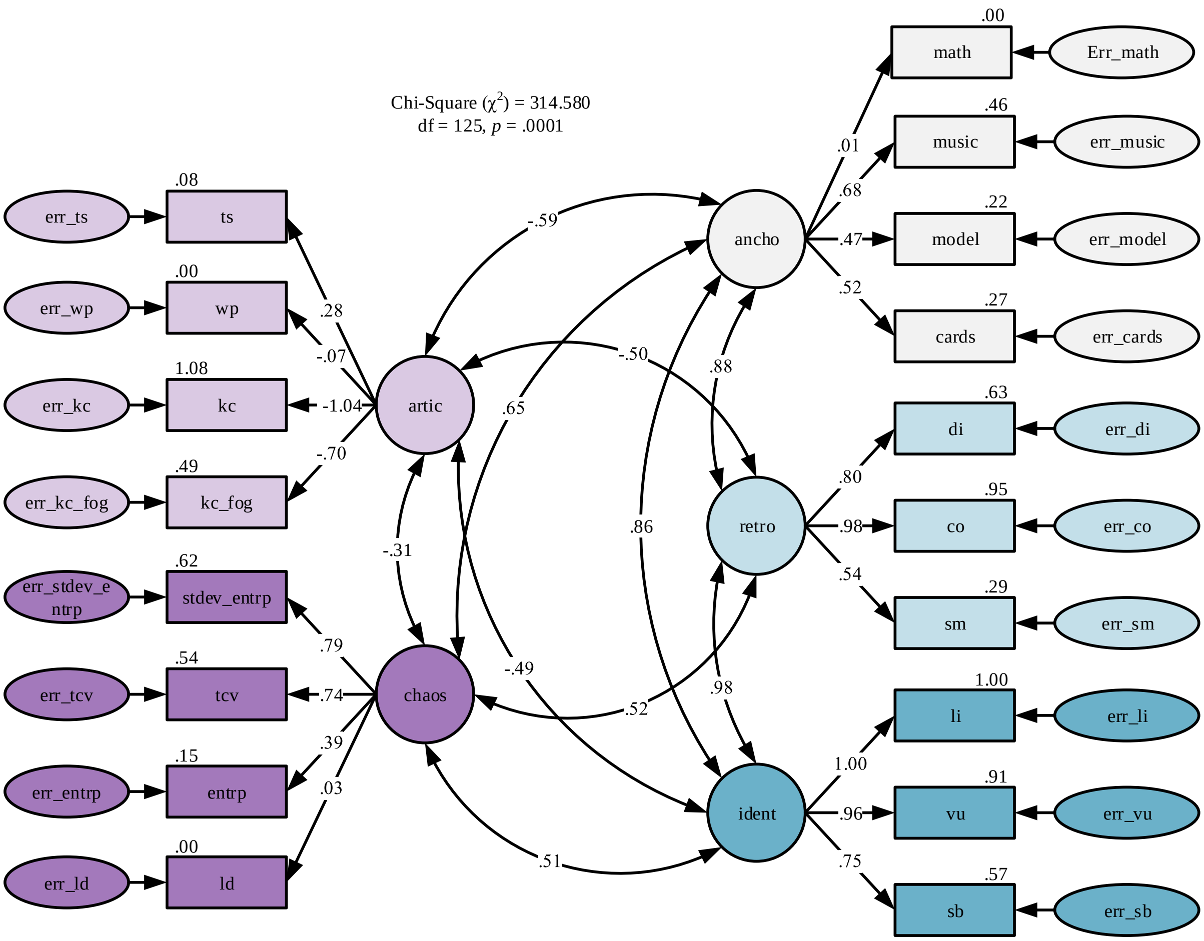


Figure 15. Model A: Initial CFA Model

Model B Analysis

Four indicators have been removed based on low regression weights: content length (ts), words per minute (wp), loudness (ld) and math (math). These indicators have been removed as they exhibit no statistical significance (See Figure 16. Model B: Tuned CFA Model). In addition, the anchoring construct illustrated a candidacy for item parceling. In 'item parceling', "...researchers may combine item-level responses into aggregate item parcels to use as indicators in a structural equation modeling context." (Hall, Snell, and Foust, 1999). There are explanatory downsides to item parceling. The ability to distinguish regression weights between the combined constructs is a factor (Bandalos and Finney, 2001). However, given the nature of the anchoring construct -

anchoring combinations are valid as well. The use of item parceling in this context does not diminish the overall explanatory nature of the model. The tuned CFA model has a chi-square of 108.892, 54 degrees of freedom and a normed chi-square of 2.017 (See Table 5. Model B Reliability). These values are considered very good. In addition, the model *p*-value is measured well below the 0.05 threshold. The overall measures of fit illustrate a much better model that nearly fits across all model metrics. The Normed Fit Index, Tucker-Lewis Index and Comparative Fit Index are all above the 0.95 threshold. The Relative Fit Index and Goodness-of-Fit Index are only marginally below the 0.95 threshold. Akaike's Information Criterion (AIC) is a measure of model information loss. Less information loss indicates a higher quality model (Sakamoto, Ishiguro, and Kitagawa, 1986). A lower AIC value relative to the initial model value (314.580 to 108.892) illustrates that the tuned model is of a higher quality.

Model B: Average Variance Extracted (AVE)					
Indicators	artic	retro	ident	chaos	ancho
~~ts~~	~~0.270~~				
~~wp~~	~~-0.080~~				
kc	1.00				
kc_fog	0.710				
di		0.800			
co		0.970			
sm		0.540			
li			0.990		
vu			0.950		
sb			0.760		
stdev_entrp				0.770	
tcv				0.760	
entrp				0.380	
~~ld~~				~~0.040~~	
~~math~~					~~0.010~~
mumo					0.980
camo					0.860
AVE > 0.50	**75.21%**	**62.42%**	**82.01%**	43.83%	**85.00%**
CR > 0.60	**85.50%**	**82.56%**	**93.11%**	**68.40%**	**91.86%**

Table 5. Model B Reliability

The Average Variance Extracted (AVE) now indicates that four of the five latent constructs are reliable (e.g., articulation, anchoring, retrospection, identity). The chaos construct is borderline. It exhibits adequate construct reliability; yet, the AVE is below the required 50% threshold. The entropy dimension exhibits a low regression weight in this model and will be removed in the next phase. Overall, this CFA model can proceed to the structural modeling phase.

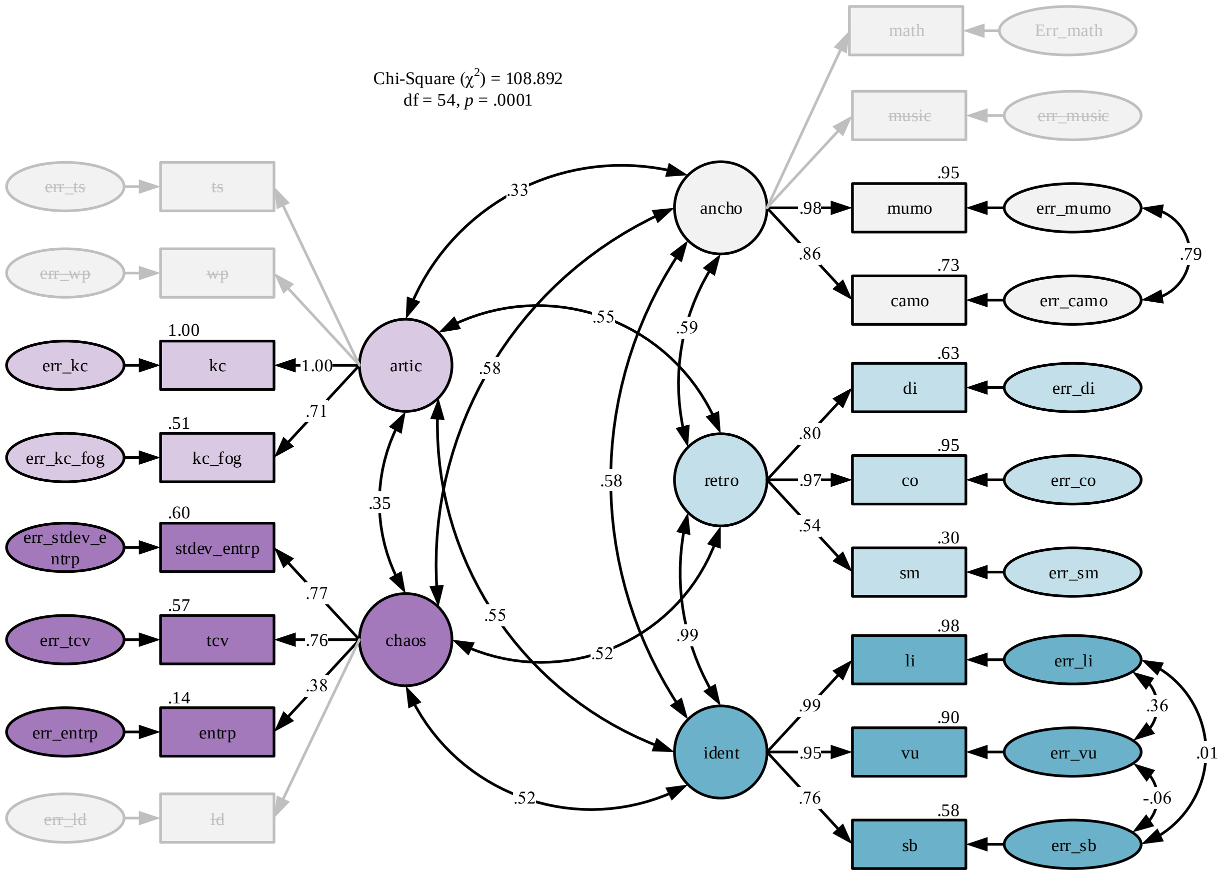


Figure 16. Model B: Tuned CFA Model

The Design of Model C: Considerations & Construction

The final model (Model C) was constructed based on the analyzed behavior of the measured parameter estimates. When converting a CFA model into a structural model, the parameter estimates are analyzed differently. CFA is a frequent first step to evaluate the anticipated measurement model in a structural equation model. The interpretive guidelines concerning the assessment of model fit and modification in structural equation modeling (SEM) apply similarly to CFA. However, CFA is distinguished from SEM in that CFA contains bidirectional arrows between the latent constructs. CFA factors are not presumed to have correlative causation (i.e., the factor estimates in CFA merely express the existence of explainable variance between the latent constructs in question). On the other hand, SEM illustrates the correlative causal relationship with directed arrows. These directed arrows have values called parameter estimates. These parameter estimates are regressive in that they are predictive (Muthén and Muthén, 2009). While SEM and CFA work together to provide insight, they are two distinct statistical processes. In summary, CFA is a *non-predictive* measurement model; SEM is the *predictive* structural model. SEM is not always predictive (i.e., usage of PLS-SEM vs CB-SEM). However, this covariance-based model of SEM utilizes the SPSS AMOS toolset. AMOS computes a regression weight between the various latent contructs allowing for predictive assessments to be made (as opposed variance weight, a strict causal measure).

What does that mean for the construction of Model C? First, Model C is a predictive path model. The factor relationships in Model A and B are not predictive in nature. They are measurement models. Second, in constructing the final path model multiple model variants were explored. Third, explainable variance in Model B may not translate into regressive correlations in Model C. Finally, observed regressive correlations with parameter estimates above 0.30 were persisted in the final structural model. An evolutionary analysis of the models is reviewed in Chapter 6 – Discussion (See Figure 19. Evolution of Structured Sensemaking Model).

Model C Analysis (Structural Model)

One indicator has been removed based on a low regression weight: entropy (entrp); however, the standard deviation of entropy was maintained in the model. The tuned SEM model has a chi-square of 69.680, 47 degrees of freedom and a normed chi-square of 1.483 (See Table 6. Model C Reliability). These values are considered excellent. The model's *p*-value has increased and is measured at 0.017. The slight increase is notable; however, it is still well below the 0.05 threshold. The overall measures of fit illustrate fits across all model metrics. The Normed Fit Index, Tucker-Lewis Index, Relative Fit Index, Goodness-of-Fit Index, and Comparative Fit Index are all above the 0.95 threshold. The Standardized Root Mean Squared Residual (SRMR) is measured at 0.047 and is below the 0.08 threshold. The Root Mean Square Error of Approximation (RMSEA) is also measured at 0.047 and is well below the lower 0.05 threshold of the metric. Akaike's Information Criterion (AIC) is measured at 131.680 and is the lowest across all three models. This indicates that the final structural model exhibits the lowest loss of information and also indicates that Model C is of the highest quality when compared to the other models (Sakamoto, Ishiguro, and Kitagawa, 1986).

Model C: Average Variance Extracted (AVE)					
Indicators	artic	retro	ident	chaos	ancho
~~ts~~	-				
~~wp~~	-				
kc	0.920				
kc_fog	0.780				
di		0.790			
co		0.980			
sm		0.540			
li			0.990		
vu			0.950		
sb			0.770		
stdev_entrp				0.770	
tcv				0.790	
~~entrp~~				-	
~~ld~~				-	
~~math~~					-
mumo					0.870
camo					0.760
AVE > 0.50	**72.74%**	**62.54%**	**82.01%**	**60.85%**	**66.73%**
CR > 0.60	**84.13%**	**82.60%**	**93.11%**	**75.66%**	**79.97%**

Table 6. Model C Reliability

The Average Variance Extracted (AVE) now indicates that all five latent constructs are reliable (e.g., chaos, articulation, anchoring, retrospection, and identity). Conclusions can now be made given the structural model metrics observed (See Figure 17. Model C: Tuned SEM Model).

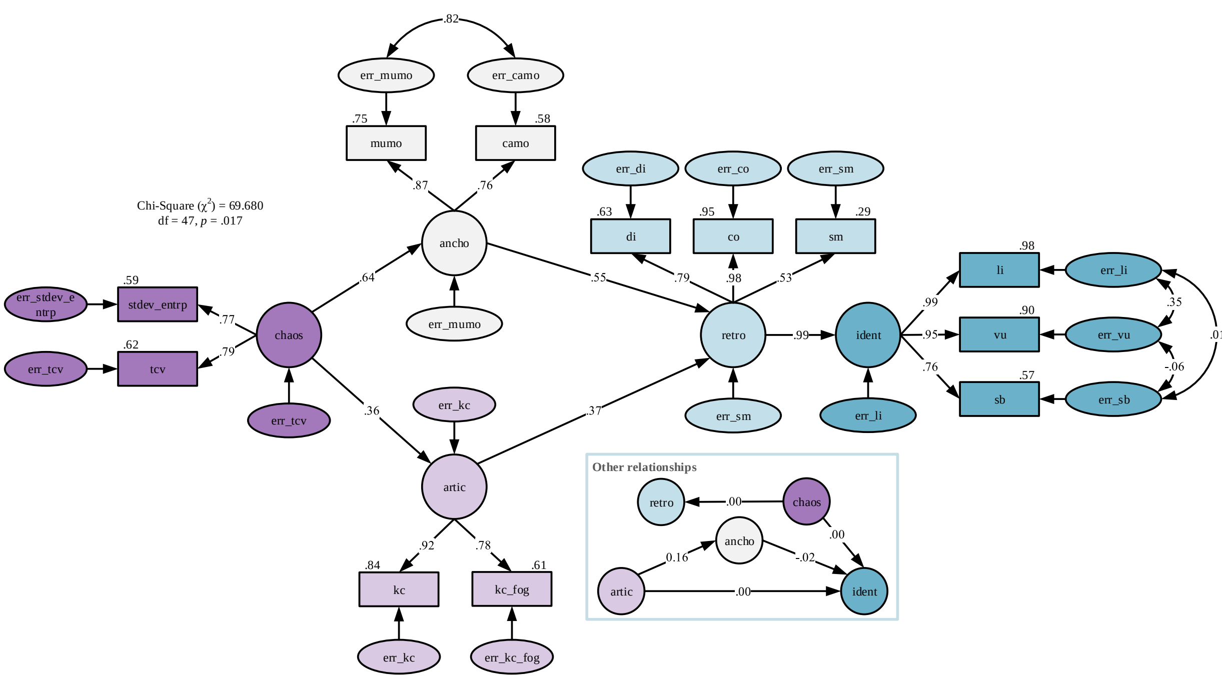


Figure 17. Model C: Tuned SEM Model

Overall Model Analysis

Both factor and structural model properties are as follows: each model was built using a maximum likelihood estimation method, covariances supplied as inputs were unbiased, and the number of permutations was set to 500. The analysis section is grouped into a summary and detail.

Summary of Hypotheses (See Figure 18. Tested Causal Model):

Of the 10 hypotheses, 7 hypotheses were accepted, and 3 hypotheses were rejected.

- H1. The articulation of content has a positive effect on identity behavior - Reject
- H2. The articulation of content has a positive effect on retrospection behavior - Accept
- H3. Retrospection behavior has a positive effect on identity formation - Accept
- H4. Anchoring of content has a positive effect on identity formation - Reject
- H5. Anchoring of content has a positive effect on retrospection behavior - Accept
- H6. Chaos has a positive effect on the anchoring of content - Accept
- H7. Chaos has a positive effect on the articulation of content - Accept
- H8. Chaos has no effect on identity formation - Accept
- H9. Chaos has no effect on retrospection behavior - Accept
- H10. Articulation of content has a positive relationship on the anchoring of content – Reject

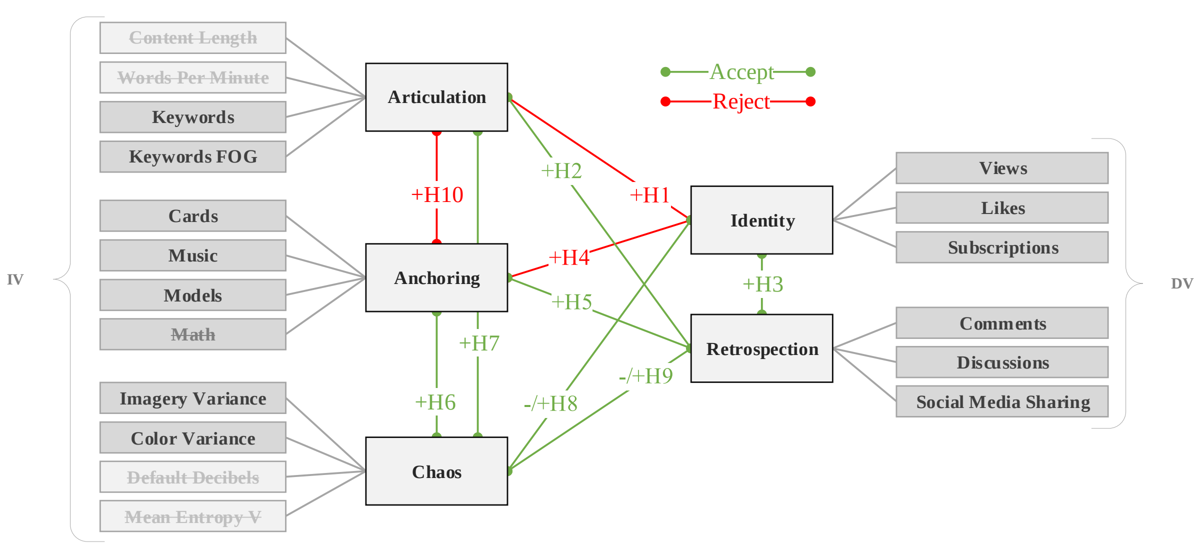


Figure 18. Tested Causal Model

Factor Correlations of Model C			Estimate (>0.30)	p-Value (<0.05)
Anchor	< >	Chaos	**0.639**	**0.001**
Articulation	< >	Chaos	**0.362**	**0.001**
Retrospection	< >	Anchor	**0.551**	**0.001**
Retrospection	< >	Articulation	**0.372**	**0.001**
Identity	< >	Retrospection	**0.993**	**0.001**

Model C Indicator Reliability (by Factor)			Estimate (>0.50)	Squared Correlations (>0.50)
Identity (ident)	>	Views (vi)	**0.946**	**0.896**
	>	Likes (li)	**0.989**	**0.979**
	>	Subscribers (sb)	**0.756**	**0.572**
Retrospection (retro)	>	Comments (co)	**0.975**	**0.951**
	>	Discussions (di)	**0.792**	**0.628**
	>	Social Media Sharing (sm)	**0.538**	0.289
Articulation (artic)	>	Keywords (kc)	**0.916**	**0.839**
	>	Keywords FOG (kc_fog)	**0.784**	**0.615**
Chaos (chaos)	>	Imagery Variance (stdev_entrp)	**0.768**	**0.589**
	>	Color Variance (tcv_v)	**0.787**	**0..620**
Anchor (ancho)	>	Cards & Models (c_ancho_camo)	**0.759**	**0.577**
	>	Music & Models (c_ancho_mumo)	**0.866**	**0.750**

Table 7. Model C Construct-Indicator Metrics

Review of Hypotheses: The Results

H1. The articulation of content has a positive effect on identity behavior - Reject

Relationship: artic <> ident | CFA - Accept (0.55) | SEM - Reject (0.00)

The null hypothesis cannot be rejected. The measured parameter estimate between these two sensemaking constructs did not indicate any relationship at the SEM level (Model C). The initial belief was that the articulation of content (e.g., the attributes associated with the video itself) would have a positive relationship to identity formation. The data does not statistically substantiate this relationship. The tuned CFA model (Model B) shows a statistical significance between these two constructs; however, the SEM model does not show a statistical significance.

H2. The articulation of content has a positive effect on retrospection behavior - Accept

Relationship: artic <> retro | CFA - Accept (0.55) | SEM - Accept (0.37)

The Articulation to Identity relationship presents an interesting case. This latent construct required tuning. The content length as well as the words per minute were found to be not statistically significant. However, the keyword usage indicator has a high squared correlation (see Table 7. Model C Construct-Indicator Metrics). The keywords were then evaluated for readability using Gunning's Fog Index (FOG) (Gunning, 1969; Skierkowski et al., 2018). This was then added into the articulation construct and this improved the construct's reliability. The articulation construct via keyword usage and keyword readability showed a positive correlation to that of retrospective behaviors. Increased levels of articulation associated to a video can be used to predict retrospection behavior (e.g., if high levels of articulation exist, then high levels of retrospection behavior also exists [in the context of a social computing platform]).

H3. Retrospection behavior has a positive effect on identity formation - Accept

Relationship: retro <> ident | CFA - Accept (0.99) | SEM - Accept (0.99)

Both CFA and SEM models illustrated a strong positive covariance between retrospection behavior and identity behavior. This relationship maintained its statistical significance across all three models (Model A, B, and C). This finding reinforces theories in product development that illustrate the creation of shared stories as central to product popularity. Furthermore, this finding demonstrates that narrative retrospection on a social computing platform has a direct positive effect on identity. In addition, the study illustrates the strength of the following indicators: likes, views, subscribers, comments, and discussions. The presence of retrospective activities associated to a video can then be used to predict identity formation (e.g., if high levels of retrospection exist, then high levels of identity formation also exist [in the context of a social computing platform]).

H4. Anchoring of content has a positive effect on identity formation - Reject

Relationship: ancho <> ident | CFA - Accept (0.58) | SEM - Reject (-0.02)

The null hypothesis could not be rejected in this case. The anchoring construct required model tuning via item parceling (Hall, Snell, and Foust, 1999). In this case, music and models were combined into a single indicator (mumo). Cards and models were also combined into a single indicator (camo). In addition, the math indicator was removed as it showed no statistical significance. While the covariance between these two parceled indicators is measured at 0.82 (lower is better), the explanatory nature is not completely lost (a risk when item parceling in SEM). This serves to boost construct reliability; however, this comes at a cost in regards to indicator analysis (e.g., the sum of cards, music, and models is variant, yet, the top variant is unknown). While the tuned CFA model (Model B) indicates a statistically significant relationship does exist, the tuned SEM model (Model C) indicates no statistical significance between the anchoring of content and identity formation. This hypothesis was rejected based on divergent model metrics.

H5. Anchoring of content has a positive effect on retrospection behavior - Accept

Relationship: ancho <> retro | CFA - Accept (0.59) | SEM - Accept (0.55)

Both CFA and SEM models exhibit statistical correlations between the anchoring of content and retrospection of content. Models, Music, and Cards have statistical significance (models being core to both parceled indicators). The music and models indicator (mumo), exhibit a higher regression value (0.75) versus the cards and models indicator (camo). This tells us that music and models are more strongly associated with retrospection with cards being the least correlated (i.e., given that both parceled indicators share models). The presence of music and models within a video can then be used to predict retrospective behavior (e.g., if music and models are present, then retrospective behavior increases [in the context of a social computing platform]).

H6. Chaos has a positive effect on the anchoring of content - Accept

Relationship: chaos <> ancho | CFA - Accept (0.58) | SEM - Accept (0.64)

Chaos has a positive effect on the anchoring of content. This is a significant finding within the research. As this relationship links two different sensemaking theories: the idea of chaos (from Weick) and the idea of anchoring (from Klein) are procedurally relevant. The strength of this relationship indicates that the deviation of entropy as well as the total color variation has a positive effect on the usage of music, models, and cards within a video. The relationship may be described more appropriately as a "managed" relationship between these two constructs (e.g., more content variation leads to the creation of more anchors necessary to manage the incoming stream of data from the video).

H7. Chaos has a positive effect on the articulation of content - Accept

Relationship: chaos <> artic | CFA - Accept (0.35) | SEM - Accept (0.36)

Like hypothesis six, this finding merges two different theories of sensemaking. While the CFA factor loading is measured at 0.35, the statistical significance of the lower factor loadings is relevant given the model's low *p*-value (See Figure 16. Model B: Tuned CFA Model). The strength is not as strong here as it is with anchoring of content (i.e. the SEM *p*-value indicates a 99% confidence that 36% of the variance is explainable, which is statistically significant). And like hypothesis six, this relationship may be described more as a "managed" relationship (e.g., more content variation leads to the creation of more keywords - and readable keywords - necessary to manage and index the incoming stream of data from the video).

H8. Chaos has no effect on identity formation - Accept

Relationship: chaos <> ident | CFA - Reject (0.52) | SEM - Accept (0.00)

Chaos does not have any effect on identity formation. This makes sense as the content must exist before identity formation can even occur. While a statistically significant factor loading in CFA was found, this statistically significant variance in SEM was not. This finding informed the final state of the structural path model (e.g., chaos leads to articulation and anchoring first). This hypothesis was accepted based on the divergent model metrics that chaos has no effect on identity formation.

H9. Chaos has no effect on retrospection behavior - Accept

Relationship: chaos <> retro | CFA - Reject (0.52) | SEM - Accept (model non-convergence)

Like hypothesis eight, a relationship between chaos and retrospection behavior was not found. Much like identity, retrospection behavior must exist post content creation. This finding had an impact on the design of the structural path model (i.e., chaos does not lead to retrospection; however, based on the confirmed hypotheses of H2 and H5, anchoring and articulation lead to retrospection). Path model analysis confirmed convergence issues. Model convergence issues continued under different modeling scenarios (i.e., generalized least squares and unweighted least squares). Consequently, the parameter estimate for this relationship value was non-calculable. Due to the divergent model metrics this hypothesis is accepted.

H10. Articulation of content has a positive relationship on the anchoring of content - Reject

Relationship: artic <> ancho | CFA - Accept (0.33) | SEM - Reject (.16)

In the last hypothesis, it was determined that there is no statistical relationship between the anchoring of content and the articulation of said content. While the CFA model is acceptable, the SEM model is not. Therefore based on divergent model metrics, this hypothesis has been rejected as the null hypothesis cannot be rejected. Like hypotheses H2, H5, H8, and H9, this relationship - or non-relationship as it were - is useful in depicting the structural path model.

Chapter 6 - Discussion

This research quantitatively describes a newly formed model of structured sensemaking. This theory of structured sensemaking describes the positive relationships between five sensemaking constructs. In addition, this research also describes the lack of statistical relationships between them as well. It is through these identified and non-identified relationships that this research was able to create this new structurally focused sensemaking model. In summary, it was determined that there is a positive relationship between chaos and articulation. There is a positive relationship between chaos and anchoring. There is a non-relationship between chaos and retrospection behavior. It was demonstrated that there is a strong statistical correlation between identity formation via retrospection. Lastly, it was hypothesized that there would not be a positive relationship between identity and any other construct outside of retrospection. It was determined that identity is only associated with retrospection and no other activity within the structured sensemaking model. The final structural model has a measured *p*-value of 0.017, a Normed Fit Index of 0.973, a Tucker-Lewis Index of 0.987, a Comparative Fit Index of 0.991, a measured Standardized Root Mean Square Residual (SRMR) of 0.0470, and a Root Mean Square Error of Approximation of 0.0470. These numbers indicate a model of high quality and confidence in its conclusions.

Theory of Structured Sensemaking

This research illustrates the usefulness of a combined sensemaking framework measured via a structured equation model. First, retrospection plays a large part in fostering identity with educational content. Second, chaos has a positive effect on anchoring and articulation. Third, anchoring has a positive effect on retrospection. Fourth, articulation also has a positive effect on retrospection. Lastly, Retrospection is the strongest construct. This research documents the evolution and integration of five different sensemaking perspectives into a single quantitative research package (See Figure 19. Evolution of Structured Sensemaking Model). This study demonstrates the importance of having collaborative tools within a social computing platform that fosters retrospective behavior. In addition, there is a benefit to having a discussion mechanism peripherally related to the social computing platform itself (e.g., Reddit discussions versus YouTube comments). For organizations, increasing the identity of educational content may be achieved through collaborative mechanisms that increase dialogue. For example, the usage of a

Reddit-like function for employees who undergo training (or learning activities) may help to enhance the learner's ability to identify with the learning material. Thus, potentially enhancing the overall learning experience.

Chaos has a statistically strong relationship to the use of anchors. This relationship is strongest with musical-based and model-based video anchors. Cards were statistically significant as well. In a surprise finding, Math anchors were not statistically significant. There are indications that math-driven content can create negative feelings towards learning math (An, Kulm and Ma, 2008). Based on prior theoretical perspectives, combining math with music should positively influence learning outcomes (An, Kulm and Ma, 2008). This information would indicate a negative variance, instead it was not shown to be statistically significant in the model. A lack of statistical significance was evident even when math was combined with music (e.g., via item parceling).

Higher levels of imagery are positive related to higher levels of anchoring. More specifically, the usage of models, music, and cards is warranted in educational videos. It is also believed that this has an impact on retrospection behavior. While there is no clear relationship between chaos and retrospection behavior, the model indicates that an increase in anchoring activities leads to an increase in retrospection activities. If anchoring activities have influence via chaos (e.g., increase image variation and color variation), then the two would go hand in hand to increase retrospective activity. Consequently, the usage of models, music, and cards is useful for the development of educational videos.

The relationship between retrospection and articulation has a softer statistical relationship. It does not exhibit path loadings as high as the other relationship, but it is statistically speaking very relevant (i.e., a parameter estimate above .20 with a model p-value below 0.05 is statistically significant). Retrospection has a statistical impact on three additional constructs: anchoring, identity, and articulation. These are positive relationships. In other words, if retrospection increases, its net effect (according to the structured sensemaking framework) has a net increase in anchoring, articulation, and identity. This is an interesting phenomenon, as much of the literature is qualitative in nature and implicitly arrives at bits and pieces of this relationship (i.e., talking it over with peers, communication is key, talking is good, etc…). This research quantitative substantiates the high importance of retrospection within sensemaking. In the structured sensemaking approach, retrospection is critical. Higher levels of retrospection are healthy.

Are the relationships within the structural model mutually exclusive? The short answer is the model has both. Some relationships are exclusive, others are not. While this was not tested, mutual exclusivity can be inferred regarding the relationships within the structural sensemaking model. For example, it is not known based on research testing that identity is, in fact, exclusive to retrospection behavior. In other words, no additional statistical relationship exists. Of course, the limitation is that the constructs had to be tuned, specifically, the articulation construct was in jeopardy of being non-usable due to the statistical non-significance of words per minute and content length. However, it turns out that keywords, and keyword readability, exhibited a strong statistical relationship to overcome the deficiencies found in the other two indicators.

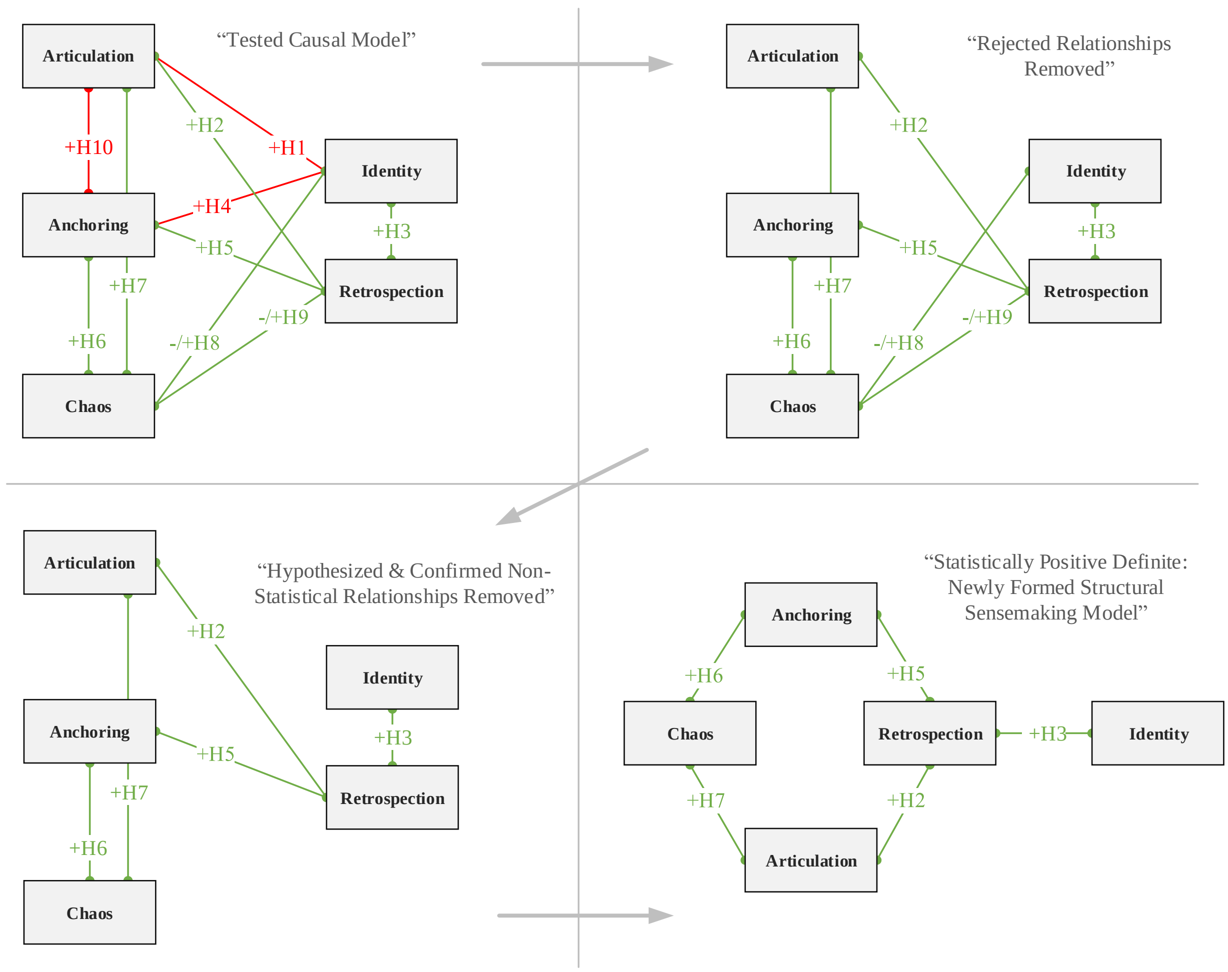


Figure 19. Evolution of Structured Sensemaking Model

While the model does tend to exhibit a starting point, that being the latent chaos construct, it does not necessarily mean it begins with chaos and ends with identity. This structured sensemaking model does not flow in a linear fashion, it is multidirectional and temporal (i.e., slices of sensemaking). For example, identity influences retrospection, it is not unidirectional in that retrospection only impacts identity. Anchoring and articulation impact chaos, retrospection impacts anchoring and articulation. These construct relations indicate that the model is not unidirectional.

While the research is limited to videographic content, the structured sensemaking framework should be tested in textually rich environments. The research scope is narrowly defined in this regard. Quantitative analyses have strength in demonstrating statistical relationships and developing predictive outputs, it does not provide a detailed reason as to "why" these relationships exists. The anchoring construct was parceled. This parceling helped to increase the structural parameter estimate values in addition to increasing the regression weights. However, in so doing, some predictive power was lost due to this item parceling. It is recommended that each latent construct have at least three or more indicators, and no less than two indicators per latent construct. While this model maintains these thresholds, it could be enhanced. It is useful to know the relationship between the keywords and the readability of keywords as it relates to retrospection behavior. In addition, the articulation construct could be further enhanced with more indicators. The same can be said for the latent anchor construct.

For future research, a qualitative analysis could be pursued to help answer how these construct relationships are forming. Second, the latent constructs can be expanded to include more indicators. For example, to name a few: external links could be added to retrospection (as user linking behavior is also an element of retrospective behavior), models and music can be broken down into lower-level categories (classical music, rock music, graphs, tables, pictures, etc…), and Kolmogorov entropy (as opposed to the classical Shannon entropy) (e.g., there are different versions of entropy that could also be added to the chaos construct). In addition, a special user interface test case involving entropy was devised but not tested (See Appendix C – Final Construct-Indicator Map).

For every indicator added and additional 10 samples are required, expanding the data sample would be advisable as the number of indicators was increased. Operationalizing structural equation models using SPSS AMOS and SQL is was very helpful. Packages such as Lavaan in R and FactorAnalyzer in Python lacked the necessary quality and visualizations to do this analysis properly. SPSS AMOS is tested and the results can be trusted. However, the operationalization of SEM using SPSS AMOS is not possible at this time. Operationalizing the structural equation modeling process can enhance design science methodologies looking to use structural equation models for real-time decision support, to this day, nothing like this currently exists.

The generalizability of this research is limited by the computing platform (e.g., social computing via YouTube) and the narrowly defined content under observation (e.g., educational videos). Additional research should be conducted to determine the bounds of generalizability (i.e., sensemaking of other content types and in other systems). In the future, this latent sensemaking framework will expand to include sensemaking constructs that encompass the use of anchors and chaos (via information theory and image complexity). While YouTube is a unique social computing platform in that the content presented is expansive (video content length well beyond that of Twitter, Instagram, Snapchat and Tik Tok), the effectiveness of this latent sensemaking framework indicates that it could be applied to other social computing platforms.

Final Thoughts

In revisiting Dr. Washburn's angry Wasp. Does a wasp feel anger? Humans can only pose the question; we cannot reinforce the "shared sensemaking" circuit with the wasp. This does not indicate that the wasp does not have sensemaking powers. On the contrary, all living creatures have some form of sensemaking capabilities (e.g., plants moving with the sun or the movement of fish during low tides). Yet for all our abilities to engage in collaborative sensemaking, humans can be easily brought into false narratives and dubious retrospections. This can lead to mis-identities (i.e., emotional purchasing, political ideologies, workplace disagreements, etc…). These forces occur not just on the individual level, they occur at macro scales as well:

- Controlling of political narratives
- Creation of cult-based systems
- Creating and deconstructing factless post realities
- Sensemaking of priorities in government
- Detecting threats between multiple actors in a battlespace

This structured sensemaking model may have implications at these higher levels. News organizations process thousands of data points daily. The world around them is a chaotic one. In structuring content, news outlets have to create content that is easily digestible for broad audiences.

For example, the structuring of a political narrative is oftentimes shaped by panel discussions. These retrospections are designed to create an audience identity. It just so happens in this hypothetical case that the content is politically motivated but the sensemaking framework is still the same. This can be explained via an overlay; a hypothetical use case for structured sensemaking (See Figure 20. Hypothetical Example of Macro Sensemaking in Action). In this hypothetical use case, the structured sensemaking model is conceptualized at a macro level for a macro use case. If someone was asked to manage an explosive political story, the structured sensemaking model indicates that an information coordinator would need to create low entropy and high entropy content in the chaos phase. Anchors in the form of models and music should also be used and associated with the content. At the same time, keywords need to be defined and those keywords need to be easy to read. Retrospection mechanisms need to be created for the newsroom and the audience. Audience members then have a greater chance to identify with the content they are seeing.

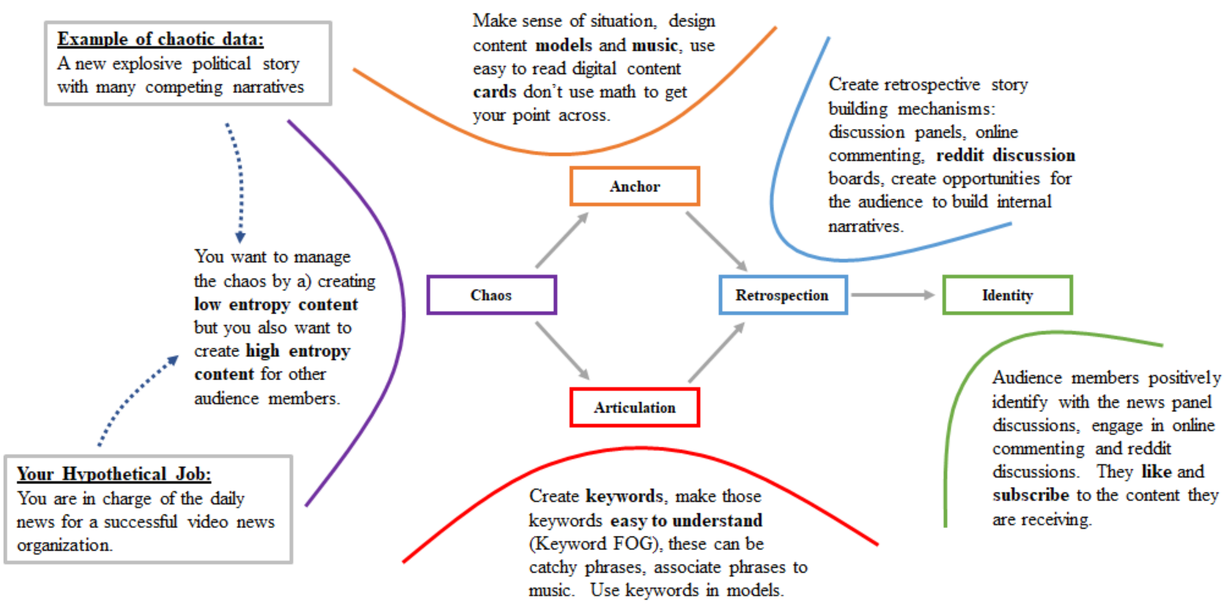


Figure 20. Hypothetical Example of Macro Sensemaking in Action

This research illustrates that retrospection is a pliable construct; the retrospection process can be influenced. For example, if a researcher wanted to purposefully drive down associations related to articulation, identification and anchoring then the researcher could influence all three constructs by limiting retrospective activity. A decrease in retrospection leads to a decrease in identification with content. Withholding the ability to retrospect chokes off the entire framework of sense-making.

In addition, chaos has a positive relationship with articulation and anchoring. Like retrospection, the researcher can influence articulation and anchoring through the chaos construct. The chaos construct is largely a measure of imagery variance as a function of information entropy. At a basic level from an applied perspective – the audience members will have a more enhanced retrospective experience – when the imagery they are seeing contains a combination of both high and low entropy variation. As an example, switching between video content that contains better use of white space (i.e., low entropy) and video content that has artwork (i.e., high entropy). This research illustrates that this variation in imagery positively influences the anchoring and articulation of content and when anchoring an articulation are enhanced they also enhance retrospective activities. In contrast, if a video were to only show two or three images throughout the entire video the entropy variation in the video stream would be defined as flat. It would not be "attention" grabbing. The chaos construct is a measurement of high and low entropy states. Regardless of the entropy state, it must have a variation to positively influence the sensemaking framework. In other words, the content should not be all high, or all low, what is relevant is that there is a continuous change between these two states throughout the video sensemaking process.

In conclusion, this research finds support for a) the integrated sensemaking framework amongst five important sensemaking constructs b) a structured sensemaking framework c) the integration of information theory and d) a reusable sensemaking method. This theory of structured sensemaking is the first of its kind. The foundational components of dataphoric space made this research possible. This research can continue into the micro-levels of individual interactions. Yet, this structured sensemaking framework can break new ground at the macro-level (e.g., testing of structured path reversals, the creation of compelling political narratives, fact avoidance patterns, or organizational threat detection). There are additional indicators to be found, additional constructs to be researched. There are many sensemaking constructs to be discovered. This research creates a base footprint for unified structured sensemaking and it will continue to contribute to the theory of dataphoric space as well as the theory of structured sensemaking.

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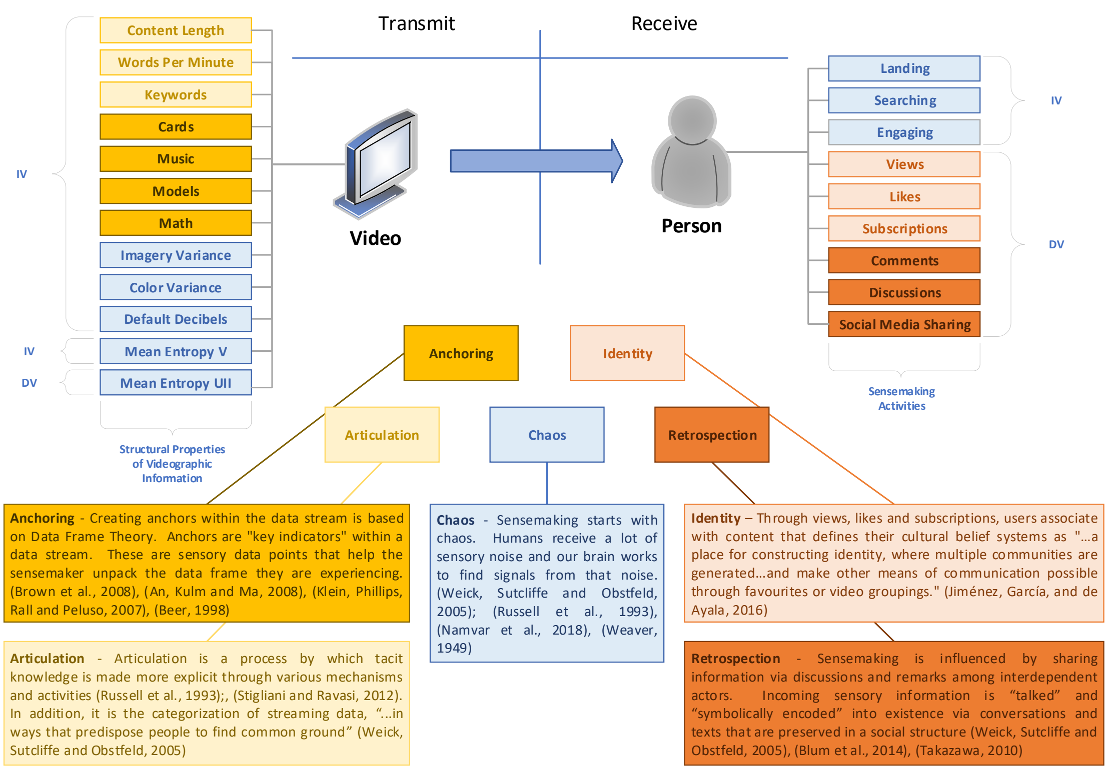
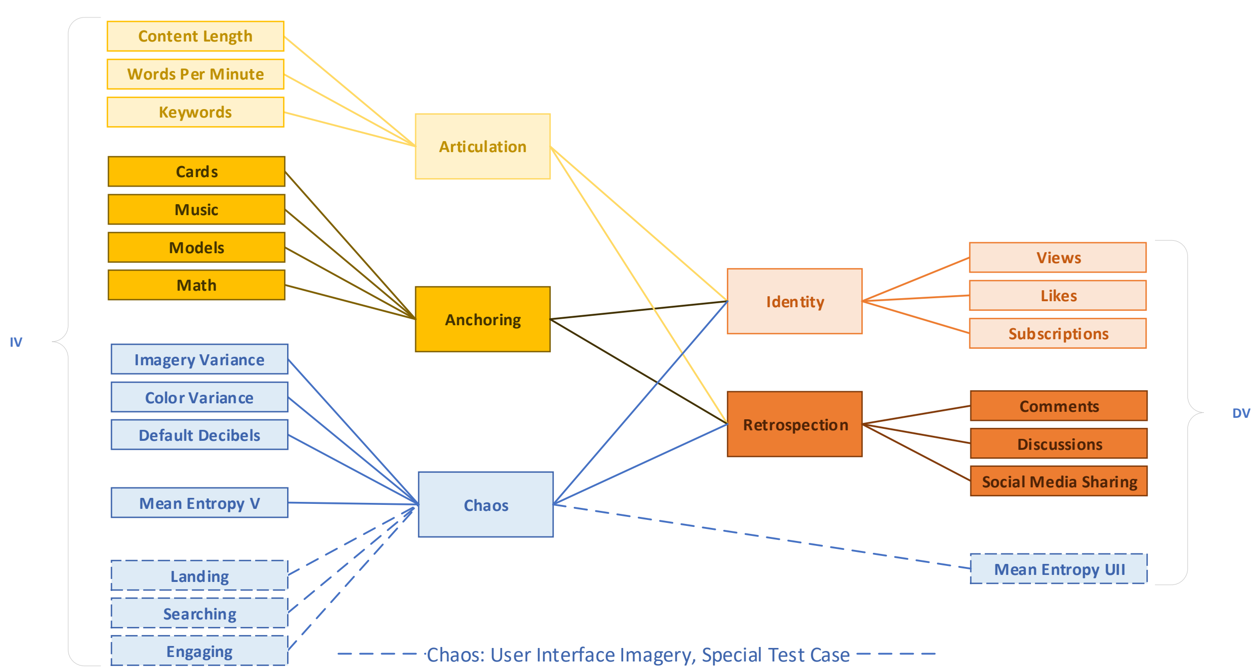
Appendices

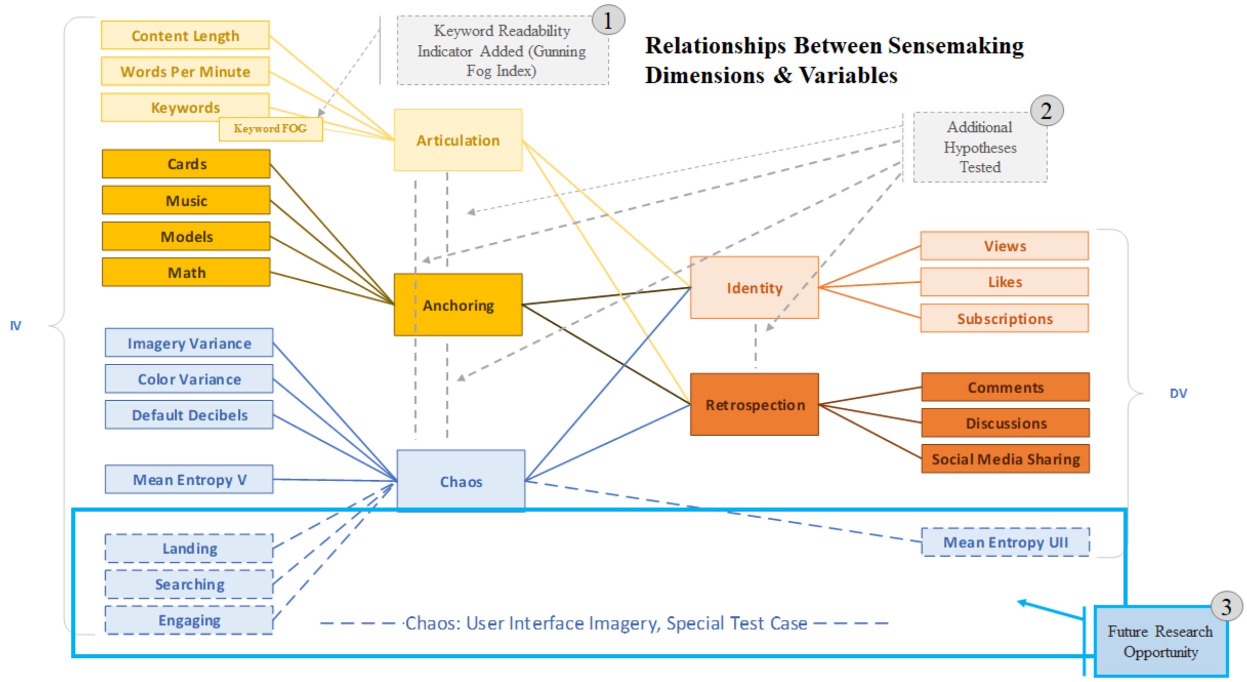
Appendix A – Original Research Proposal



Appendix B – Proposed Construct-Indicator Map



Appendix C – Final Construct-Indicator Map



Adjustments from Proposed Research to Final Research

1. The Articulation construct was adjusted to include the Gunning fog index (FOG). The Keyword FOG was added as it measures the readability of the keywords themselves. The additional metric greatly enhanced the Articulation construct.
2. In the original research proposal there were 6 hypotheses. The final research contains 10 hypotheses. During confirmatory factor analysis (CFA), it was determined that all factor relationship needed to be tested. These 4 additional hypotheses enhanced the final structural model.
3. The Landing, Searching, and Engaging indicators combined with the Mean Entropy UII feature were not tested as part of the final research. This was called the "User Interface Imagery: Special Test Case" in the original research proposal. It is indeed so specialized a test case that it warrants its own research paper.

Appendix D – Research Architecture