Fuzzy Cognitive Maps as Representations of Mental Models and Group Beliefs

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Abstract
Fuzzy Cognitive Maps (FCM) have found favor in a variety of theoretical and applied contexts that span the hard and soft sciences. Given the utility and flexibility of the method, coupled with the broad appeal of FCM to a variety of scientific disciplines, FCM have been appropriated in many different ways and, depending on the academic discipline in which it has been applied, used to draw a range of conclusions about the belief systems of individuals and groups. Although these cognitive maps have proven useful as a method to systematically collect and represent knowledge, questions about the cognitive theories which support these assumptions remain. Detailed instructions about how to interpret FCM, especially in terms of collective knowledge and the construction of FCM by non-traditional 'experts', are also currently lacking. Drawing from the social science literature and the recent application of FCM as a tool for collaborative decision-making, in this chapter we attempt to clarify some of these ambiguities. Specifically, we address a number of theoretical issues regarding the use of Fuzzy Cognitive Mapping to represent individual "mental models" as well as their utility for comparing and characterizing the aggregated beliefs and knowledge of a community.

Keywords: combining knowledge, expert knowledge, Fuzzy Cognitive Mapping, mental models, participatory modeling, systems analysis, scenario modeling

Introduction

There is a wealth of literature from the fields of cognitive science, psychology, and systems science that discusses the use of individuals' knowledge structures as representations or abstractions of real world phenomena. However, before we can begin our discussion of how Fuzzy Cognitive Mapping (FCM) contributes to these fields, we must first reconcile the various definitions and approaches in the literature used to characterize internal cognitive representations of the external world. Understanding the theoretical foundations of concept mapping, cognitive mapping, mental models and the notion of "expertise" in the elicitation of a subject's knowledge is of particular interest to our discussion on FCM construction and interpretation. Further, we discuss issues related to analyzing FCMs collected from non-traditional experts, which is a growing area of research that seeks to characterize group knowledge structure to inform community decision-making and compare knowledge variation across groups. In this chapter, we address: how FCM can be used to understand shared knowledge and what trade-offs should be considered in the selection of FCM data collection techniques.

1 Concept Mapping, Cognitive Mapping and Mental Models as Representations of Knowledge Structures

FCM has its roots in concept and cognitive mapping. Concept maps are graphical representations of organized knowledge that visually illustrate the relationships between elements within a knowledge domain. By connecting concepts (nodes) with semantic or otherwise meaningful directed linkages, the relationships between concepts in a hierarchical structure are logically defined (Novak and Cañas 2008). The argument for representing knowledge with concept maps emerges from constructivist psychology, which postulates that individuals actively construct knowledge by creating mental systems which serve to catalogue, interpret and assign meaning to environmental stimuli and experiences (Raskin 2002). Knowledge "constructed" in this manner forms the foundation of an individual's organized understanding of the workings of the world around them, and thus influences decisions about appropriate interaction with it. Influenced by cognitive psychology's developmental theory of assimilation and accommodation, as theorized by the Swiss cognitive psychologist Jean Piaget, the use of concept maps as representations of an individual's organized knowledge is further supported. According to Piaget's developmental theory of learning, individuals' assimilate external events and accommodate them to develop a mental structure that facilitates reasoning and understanding (Piaget 1983; Flavell 1996). Using this theoretical framework, concept maps can be elicited to represent an organized understanding of a general context, thereby providing an illustrative example of a person's internal conceptual structure (Novak and Cañas 2008).

Another form of structured knowledge representation commonly referred to in the social science literature is cognitive mapping. A cognitive map can be thought of as a concept map that reflects mental processing, which is comprised of collected information and a series of cognitive abstractions by which individuals filter, code, store, refine and recall information about physical phenomena and experiences. First introduced by Edward Tolman (1948) as a replication of a geographical map in the mind, the term has since taken on a new meaning. Robert Axelrod (1976) was the first to use the term in reference to the content and structure of individuals' minds, thereby shifting its applied meaning from referring to a map that is cognitive, to a map of cognition (Doyle and Ford 1999). Using Axelrod's definition, cognitive maps are visual representations of an individual's 'mental model' constructs, and are therefore analogous to concept maps that represent a person's structured knowledge or beliefs.

Although both concept and cognitive maps are often used as external representations of internal mental models, it is important to note that these graphical representations and mental models are not the same. Cognitive maps, of which FCMs are an extension, are themselves extensions of mental models, but are distinct since cognitive maps are physical constructs, whereas mental models only exist in the mind (Doyle and Ford 1999). First introduced by Craik (1943), today the notion of mental models and their utility for understanding individual and group decision-making is a widely accepted construct in the social science literature (Jones et al. 2011), and justifies the methodological appropriation of FCMs as external representations of a person's internal understanding. It is hypothesized that in order to successfully achieve a given objective, individuals must possess sufficient knowledge of their immediate environment in order to craft appropriate responses to a given decision context (Moore and Golledge 1976). In such contexts, mental models are considered to provide the structures that form the basis of reasoning (Jones et al. 2011). The perceived utility of internal mental models in decision making contexts lies in their simplicity and parsimony, which permits complex phenomena to be interrogated and salient components selected to form judgments. Inferring causal relationships between a range of factors based on available evidence or beliefs facilitates the generation of workable explanations of the processes, events and objects an individual may encounter within their environment. By encoding these inferences into a heuristic structure, individuals can accrue knowledge incrementally over time, thereby offsetting the limitations of human cognition under conditions of complexity and uncertainty (Seel and Dinter 1995). This process enables individuals to construct an internal model that both integrates their existing relevant knowledge of the world, as well as meets the requirements of the domain to be explained. To enable individuals to make a context-appropriate decision, mental models mediate between knowledge stored in the long-term memory and knowledge that is constructed in the short-term working memory (Nercessian 2008). Therefore, it is hypothesized that individuals constantly rely on mental models to structure their understanding, explain the world, and to some extent, make decisions that reflect this internal process of reasoning.

Combining the notion of mental modeling with cognitive mapping, FCM utilizes fuzzy logic in the creation of a weighted, directed cognitive map. FCMs are thus a further extension of Axelrod's definition of cognitive maps, and can therefore similarly be considered a type of mental model representation (Kosko 1986a; Özesmi and Özesmi 2004; Groumpos 2010; Jose 2010). Given FCMs may serve as semi-quantitative, detailed representations of individual and/or group knowledge structures, either through aggregation of individual's models, or through group FCM building exercises, they are attracting increased attention in applied research contexts seeking to promote collective decision-making or better understand community knowledge (Özesmi and Özesmi 2004; Amer et al. 2011; Gray et al., 2012a). Using the imprecise nature of common language, FCM permits individuals to interpret and express the complexity of their environment and experiences by combining their knowledge, preferences and values with quantitative estimations of the perceived relationships between components within a particular context of interest (Özesmi and Özesmi 2004; Lynam et al. 2007; Kok 2009; Jones et al. 2011). Similarly, from a social science research perspective, employing FCMs as representations of mental models can generate understanding of how different people filter, process and store information, as well as elucidate how these perceptions may guide individuals' decisions and actions in a particular context (Biggs et al. 2011). In a manner analogous to the mental modeling that structures an individual's cognitive decision making process, eliciting the reasoning and predictive capacity of experts' mental constructs via FCM has proven to be a useful decision support tool (Adriaenssens et al. 2004; Özesmi and Özesmi 2004; Groumpos 2010; Gray et al. 2012a). Although FCM have been proposed as a method to understand mental models, issues regarding whose knowledge is represented, how group knowledge is collected and interpreted, and what constitute best practices for combining mental models in different applied research contexts, have largely not been addressed.

2 Traditional Expertise and Non-Traditional Expertise

The collection of FCMs as representations of mental models can be divided into two general categories in terms of 'whose knowledge is being structured?'. The first, and perhaps most long standing use, is related to FCMs as representations of "traditional" expert knowledge. There is a long history of representing expert knowledge systems using FCM and fuzzy-logic in areas of research where system uncertainty is high and empirical data to validate a hypothesized model is unavailable or costly to collect. This FCM research encompasses a wide range of applications including: risk assessment (Medina and Moreno 2007; Hurtado 2010), work efficiency and performance optimization (Jose 2010; Xirogiannis et al. 2010), strategic deterrence and crisis management (Kosko 1993; Perusich 1996), scenario/policy assessment (Kok 2009; Amer et al. 2011), spatial suitability and prediction mapping (Metternicht 2001; Amici et al. 2010), and environmental modeling and management (Mackinson 2000; Hobbs et al. 2002; Adriaenssens et al. 2004; Jarre et al. 2008; Prato 2009). FCM based on expert knowledge, attempts to make tacit, expert knowledge more explicit in an effort to represent complex systems and their inherent dynamics that would otherwise not be well understood. "Experts" in this sense reflect the common use of the term and characterize social elites including physicians (Benbenishty 1992), scientists (Hobbs et al. 2002; Celik et al. 2005), and engineers (Amer et al. 2011). By collecting mental models from experts considered to hold the 'best' knowledge about a system, structure is provided to what would otherwise be loosely-linked, highly complex, or unavailable understanding of a system domain.

The second and more recently emerged category of FCMs as representations of mental models, are those collected from non-traditional experts. These FCMs are most often employed in participatory planning and management and/or environmental decision-making contexts, and are primarily used to gain an understanding of how stakeholders internally construct their understanding of their world or a particular issue of interest (Kontogianni et al. 2012a, Kontogianni et al. 2012b). For example, non-traditional expert FCMs have been elicited from bushmeat hunters in the Serengeti (Nyaki and Gray 2013), fishermen (Mackinson 2000; Wise et al. 2012; Gray et al. in press), pastoralists and farmers (Ortolani et al. 2010), as well as a range of other stakeholders during participatory planning and modeling contexts (Özesmi and Özesmi 2004; Celik et al. 2005; Kafetzis et al. 2010; Gray et al. 2012a; Meliadou et al. 2012; Papageorgiou et al. 2012). Collecting FCMs from non-traditional experts serves as a way to characterize community understanding of a system or collect data intended to help characterize a system that might not be represented by information provided by traditional experts alone (Biggs et al. 2011, Kontogianni et al. 2012a). Though there may be some degree of overlap in the need for or desire to use tacit or local knowledge to inform the decision making process, the appropriation of FCM in the collection of local stakeholder knowledge is commonly associated with decision-making in the local community context rather than to pool expert knowledge in conditions of uncertainty, where data is limited or not comprehensively linked (Kontogianni et al. 2012b). Since knowledge exists on a continuous spectrum of expertise from novice to expert, and the degree of expertise is not usually easily determined, the collection of FCMs from non-traditional experts has been largely influenced by research questions and to date, there has been little consideration of the differentiation or potential protocols of FCM collection from experts and non-traditional experts.

3 Disentangling Group Knowledge

In addition to questions associated with 'whose knowledge is being structured?', there are also research context dependent issues associated with FCM in terms of appropriately representing group knowledge. FCMs are often collected from groups of individuals and aggregated as a way to support decision-making and promote understanding of system dynamics. However, interpreting the cognitive structures of FCMs within the group context raises questions about what this pooled knowledge represents, and how it is useful for research, analysis and interpretation. Although the literature defines mental models as individual's internal representations of the world, consensus is currently lacking with regard to the theoretical basis of shared cognition as it relates to concept and cognitive mapping. Therefore, there are still questions about what collated representations of individual mental models represent (Klimoski and Mohammed 1994; Stahl 2006). In the literature, this ambiguity is demonstrated by the variable use of research methods and terms employed in the study of shared cognition (Cannon-Bowers and Salas 2001; Mohammed and Dumville 2001). To date, the FCM literature has largely ignored this ambiguity, despite the fact that FCMs are strongly influenced by the individual characteristics and cognitive processes of those who construct them (Pohl 2004), as well as the method by which they are aggregated and analyzed (Papageorgiou et al. 2006). While it is commonly accepted that individuals within a given community are exposed to the same "reality", it is also acknowledged that their interpretation of that reality may not be shared (Cupchik 2001; Stahl 2006). This is because individual mental models are socially-mediated, created with diverse knowledge abstractions, reliant on personal experience and highly dependent on prior knowledge (Seel and Dinter 1995). As evidence of this, the aggregation of individuals' knowledge structures has been shown to show considerable variation and when aggregated, the group level "knowledge structures" sometimes fail to reflect the sum of individual members' mental models (Klimoski and Mohammed 1994; Stahl 2006).

FCMs have been proposed as a unique tool for aggregating diverse sources of knowledge to represent a "scaled-up" version of individuals' knowledge and beliefs (Özesmi and Özesmi 2004). The product of the aggregation of individual's FCMs is sometimes referred to as a "social cognitive map" and is often considered a representation of shared knowledge (Özesmi and Özesmi 2004; Gray et al. 2012a). The concept of shared knowledge in the form of social cognitive maps has been used in a variety of distinct applications using of FCMs including: to gain a more comprehensive understanding of complex systems; to describe consensus in knowledge among individuals and to define differences in individual and group belief or knowledge structures. Further, as FCM evolves beyond its foundations as representations based on traditional expert systems towards the integration of more non-traditional expert knowledge for participatory engagement, it is necessary to understand the nature and appropriateness of FCM aggregation in order to ensure that interpretations are theoretically sound. Therefore, in an effort to further expand the appropriation of FCM to a new generation of social science researchers, it is of critical importance to: (1) understand what is meant by "shared" knowledge of individuals and (2) establish data collection protocols based on common FCM research goal typologies.

4 Understanding the Meaning and Measurement of 'Shared Knowledge' with FCM

There is little consensus across the literature regarding the aspects of knowledge that are shared in group decision-making (Cannon-Bowers and Salas 2001). Differences in interpretation of "shared knowledge", however, tend to emerge along disciplinary lines generated largely from the organizational behavior and social psychology literature. For example, shared team knowledge has been described as knowledge relevant to team work and task work (Rentsch and Hall 1994; Cannon-Bowers and Salas 2001) while others have referred to shared cognition as an inter-subjective process related to transactive memory shared within a community, which influences learning, and therefore, the knowledge held within a group (Mohammed and Dumville 2001). Still other researchers promote the idea of collective learning through shared frames of reference, or alternatively, through achieving consensus, which reflects shared beliefs among individuals (Axelrod 1976; Klimoski and Mohammed 1994; Stahl 2006). In essence, studies of shared knowledge highlight the importance of identifying preexisting discrete dimensions of structural and content knowledge found across individual mental models (Cannon-Bowers and Salas 2001).

In an applied research context, FCM have implications for assessing the degree of shared knowledge distributed across individuals by using a range of structural measures. Comparing FCMs allows researchers to uncover trends in reasoning, as evidenced by similarities in cognitive map structure, to be used to measure the degree of conceptual agreement. Research focused on capturing preexisting knowledge in a community seeks to understand similarities in how individuals and groups conceptualize contexts of inquiry on a systems level (Gray et al. in press, Kontogianni et al. 2012b). Understanding the degree of shared knowledge through FCM is important to explaining some aspects of social dynamics since shared knowledge is important for promoting trust, cooperation and since it may influence interaction between individuals and groups (Gray et al. 2012b).

In terms of specific structural measurements available to researchers, the last ten years have seen considerable advances in both network and FCM analyses. These advances have yielded a range of routine metrics to uncover shared knowledge structure by measuring discrete dimensions of an individual's mental model structure, thereby permitting comparisons across individuals and groups (see Table 1 for a summary) (Özesmi and Özesmi 2004; Gray et al. 2012a). Although we assume the reader is familiar with the basic FCM collection and transcription techniques of cognitive maps into matrices (Kosko 1986a), we briefly outline common measures facilitated through matrix calculations. The calculation of these measures allows the degree of shared knowledge to become estimated when the FCM modeling activity is standardized across individuals or groups. Based generally in network analysis, FCM can be analyzed for any number of dimensions, which can detect differences in how individuals view the dynamics and components in a given domain. For example, the amount of connections indicates increased or decreased structural relationships between system components or the degree of connectedness between components that influence system function and emergent properties. Centrality score of individual variables represents the degree of relative importance of a system component to system operation. Number of transmitting, receiving, or ordinary variables and the complexity scores indicate whether the system is viewed as largely comprised of driving components or whether the outcomes of driving forces are considered (i.e. that some components are only influenced). Higher complexity scores have been associated with more "expert views" of systems (Means 1985; Rouse and Morris 1985; Gray et al. in press) and therefore it is assumed that the FCMs generated by individuals with deeper understanding of a domain will have higher complexity scores relative to others with less understanding. Density scores are associated with the perceived number of options that are possible to influence change within a system as the relative number of connections per node indicate the potential to alter how a given system functions. Hierarchy scores indicate the degree of democratic thinking (McDonald 1983), and may indicate whether individuals view the structure of a system as top-down or whether influence is distributed evenly across the components in a more democratic nature. Centrality scores for an overall FCM indicate the overall perceived degree of dynamic influence within a system.

Although the implications for understanding shared structural knowledge through FCM are somewhat straight forward given the structural metrics available, understanding the degree of shared content knowledge using FCM is not quite as

Table 1. Structural metrics that can be applied to matrix forms of FCMs (adapted from Gray et al. in press)

Mental Model Structural Measurement	Description of Measure and Cognitive Inference
N (Concepts)	Number of variables included in model; higher number of concepts indicates more components in the mental model (Özesmi and Özesmi 2004)
N (Connections)	Number of connections included between variables; higher number of connections indicates higher degree of interaction between components in a mental model (Özesmi and Özesmi 2004)
N (Transmitter)	Components which only have “forcing” functions; indicates number of components that effect other system components but are not affected by others (Eden et al.1992)
N (Receiver)	Components which have only receiving functions; indicates the number of components that are affected by other system components but have no effect (Eden et al.1992)
N (Ordinary)	Components with both transmitting and receiving functions; indicates the number of concepts that influence and are influenced by other concepts (Eden et al.1992)
Centrality	Absolute value of either (a) overall influence in the model (all + and – relationships indicated, for entire model) or (b) influence of individual concepts as indicated by positive (+) or negative (-) values placed on connections between components; indicates (a) the total influence (positive and negative) to be in the system or (b) the conceptual weight/importance of individual concepts (Kosko 1986a). The higher the value, the greater is the importance of all concepts or the individual weight of a concept in the overall model
C/N	Number of connections divided by number of variables (concepts). The lower the C/N score, the higher the degree of connectedness in a system (Özesmi and Özesmi 2004)
Complexity	Ratio of receiver variables to transmitter variables. Indicates the degree of resolution and is a measure of the degree to which outcomes of driving forces are considered. Higher complexity indicates more complex systems thinking (Eden et al.1992; Özesmi and Özesmi 2004)
Density	Number of connections compared to number of all possible connections. The higher the density, the more potential management polices exist (Özesmi and Özesmi 2004; Hage and Harary 1983)
Hierarchy Index	Index developed to indicate hierarchical to democratic view of the system. On a scale of 0-1, indicates the degree of top-down down (score 1) or democratic perception (score 0) of the mental model (McDonald 1983)

clear. In their review, Cannon-Bowers and Salas (2001) outline that shared content includes aspects of knowledge such as task knowledge (both declarative and procedural), contextual knowledge, attitudes, beliefs, expectation and predictions. Although these dimensions of knowledge are more tightly linked to the team decision-making literature, there are still general implications for FCM, however this research area of FCM is somewhat underdeveloped. For example, comparing the outcomes of scenario analyses across several FCM through "clamping" the same variables (Kosko 1986a) may allow for qualitative interpretation of how a domain may react under an established pre-set condition to be compared. By evaluating these scenario outputs, researchers can make inferences regarding the degree of shared expectations and predictions across individual mental model or different aggregated group models. Additionally, coding or grouping FCM variables into discrete categories may provide a useful means by which agreement or concurrence in a particular problem and for a given system can be identified and assessed. Employing complementary tools, such as standardized surveys, may facilitate the assessment of attitudes and beliefs which could correlated with quantitative FCM structural measurements (Gray et al. in press, Kontogianni et al. 2012b). When used in tandem, such an approach may improve understanding and help disentangle the interaction between of structural and content knowledge, and develop more robust assessments.

5 Research Aim: Toward Typologies and Trade-offs of FCM Data Collection

In addition to ambiguities associated with FCMs as representations of mental models and their implications for understanding and measuring shared knowledge, the literature to date has also not dealt with the issue of knowledge heterogeneity or routine variations of FCM collection procedures toward differing research goals. The theory behind both mental models and FCM suggest that their usefulness for decision-making significantly depends upon the quality of knowledge used in their construction (Kosko 1986b; Taber 1991). Consideration of the potential implications of integrating diverse sources of knowledge using FCMs is timely, particularly given their utility as a participatory modeling approach as a tool for operationalizing diverse sources of knowledge for improved system understanding, multi-objective multi-stakeholder decision support and expansion to investigate general community understanding (Kontogianni et al. 2012a, Kontogianni et al. 2012b; Gray et al. 2013). Additionally, assessments of expert selection methods, qualification of expert knowledge, and assessment of knowledge quality are currently lacking (Davis and Wagner 2003). In an effort to provide some clarity on these issues, we identify 4 possible FCM collection strategies related to individual map collection and group map generation using freely associated or predetermined/standardized concepts (Table 2). Further, we outline the research goals afforded by each method and compare the tradeoffs of each FCM collection technique.

Table 2. Tradeoffs of different FCM data collection techniques

Model Collection Technique	Aggregation Technique	Methodological Tradeoffs
Individual Mental Model: Standardized concepts provided	Average individual FCMs together; assessment of expertise and weighting individual FCMs may be required for small sample sizes** (Cannon-Bowers and Salas 2001)	**Pros** • Aggregated models permit standardized functional analysis and scenario modeling • Careful expert selection can improve model exactness and reduce sample size demands • Standardization of concepts allow for large sample sizes to be collected and aggregated to draw conclusions about the knowledge of large communities • Standardized concepts facilitate ease of aggregation **Cons** • Model element chosen may not reflect full range of system components perceived by individuals • Interviews required first to generate list of standardized components • Multi-person multi-objective decision making validity dependent upon concept and expert selection • Constraining model components may bias FCM construction and significantly constrain representation of a domain
Individual Mental Model: Concepts chosen freely by individuals	Researcher subjectively condenses individuals mental model concepts and then averages individual mental models together to produce a group model	**Pros** • Facilitates equitable multi-person multi-objective decision making across diverse knowledge domains to be guided by the individuals constructing the model (Kosko 1986a; Carley and Palmquist 1992) • Model confidence requires larger sample sizes determined by an accumulation curve (Özesmi and Özesmi 2004) • Allows for full representation of domain components as perceived by individuals • Weighting is not necessary with sufficiently large sample sizes **Cons** • Larger role of the researcher in interpreting and condensing domain components when group model is developed • Concept condensation is time intensive and subjective • Group validation of aggregated model required to ensure representativeness • Sufficient sample size may be costly to collect
Group Model: Standardized concepts provided to group and collectively modeled	Group creates model together, percent agreement may be useful for deciding group model structure (Cannon-Bowers and Salas 2001)	**Pros** • Time efficient data collection compared to allowing groups to select concepts or individual mental model collection • Providing concepts allows for scaffolding of group model building • Real-time revision of model is possible as participant time allows • Detailed discussion of structural agreement possible • Facilitates social learning **Cons** • Group members should be experts in the domain of inquiry since the provision of predefined concepts limits the capture of variability in individuals' knowledge/ideas

Model Collection Technique	Aggregation Technique	Methodological Tradeoffs
Group Model (Continued)		**Cons (con't)** • Model's meaning is limited to the group context since socially constructed, negotiated, and validated (Klimoski and Mohammed 1994) • Knowledge represented dependent upon group power dynamics (Siebenhuner 2004; Reed 2008) • Expert facilitation skills necessary to moderate group dynamics and ensure group model is not biased toward views of more vocal/forceful individuals
Group Model: Concepts chosen by individuals, but condensed and modeled collectively	Concept brainstormed then condensed, group creates model together; percent agreement may be useful for deciding group model structure (Cannon-Bowers and Salas 2001)	**Pros** • Accommodates diverse knowledge domains of group members, pools unconstrained knowledge into map construction • Time efficient compared to individual mental model collection • Facilitates social learning **Cons** • Model's meaning is limited to the group context since it is socially constructed, negotiated, and validated (Klimoski and Mohammed 1994) • Knowledge represented dependent upon group power dynamics (Siebenhuner 2004; Reed 2008) • Expert facilitation skills necessary to moderate group dynamics and ensure group model is not biased toward views of more vocal/forceful individuals • Group modeling activity and map may deviate from original domain slightly given conceptual freedom and group dynamics

5.1 Collecting Individual FCM or Facilitating Group Modeling?

FCM and other cognitive mapping techniques have a unique methodological history since they can be used both as an assessment and measurement tool for use in applied research, but can also serve as an intervention to promote model-based reasoning and social learning in group settings. Differences in their appropriation are partially determined on the basis of whether FCM are constructed by individuals to be analyzed and manipulated by researchers, or whether groups construct them socially as an external representation and revision of shared knowledge.

In an applied research context, the difference between individual and group map creation rests on the research context, which may seek to characterize individual or community understanding, promote social learning, or a mixture of the two (see Figure 1). The strengths of individual model development include the ability of the researcher to standardize and aggregate model variables at will, as well as the ability to ensure that the resulting model representation meets the research goals. Since the collection of individual FCMs are not influenced by group dynamics, which can often be prone to power struggles, individual models provide a more robust representation of individual understanding, reveal differences in individual concepts, and highlight unbiased consistencies or inconsistencies in knowledge through comparison. This potentially allows for more equitable knowledge representation, which may more accurately characterize collective knowledge compared to group map construction. However, collecting individual FCMs may be resource intensive, and knowledge heterogeneity across maps may complicate aggregation and related structural and scenario-based analyses.

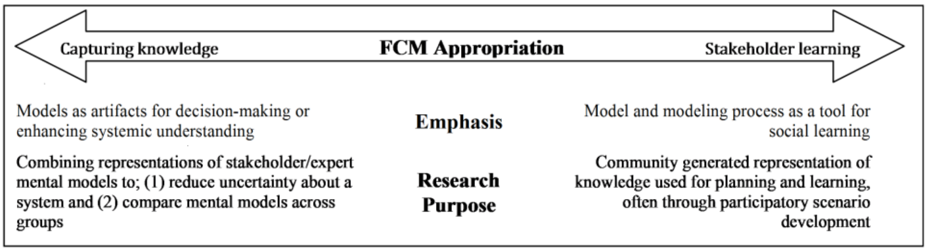

Fig. 1. Conceptual model of spectrum of FCM appropriation

Conversely, an alternative option is to engage in group modeling, whereby a group of participants constructs an FCM as a collective. Group FCM construction is most often aligned with research priorities that seek to promote and represent the outcome of social learning. In these research contexts, more emphasis is placed on model building as a process, and less emphasis placed on capturing individual-level representations of knowledge. The FCM is therefore an outcome of social interaction and represents the group construction of knowledge, achieved through the collective sharing of aspects of individuals' mental models. Group modeling is often less resource intensive compared to the collection of individual models since members of a community can be organized to create a model in a workshop or group setting. In these cases, model aggregation reflects community knowledge, and the role of the researcher is less pronounced since more control of group knowledge representation is afforded to the community. Given that the integration of individuals' knowledge structures is socially negotiated in the group model context, the resulting consensus model is ultimately dependent upon the personalities, strength of expertise, relationships and level of equality of the group. It may, however, be difficult to accurately assess the distribution of contributed knowledge across group membership or weight each member's expertise. In such contexts, the resulting FCM is most appropriately used as a tool for creating consensus related to the context of inquiry, and for facilitating group discourse for the promotion of shared understanding and collective learning. The model itself represents a socially negotiated form of collective knowledge that can be used to represent community understanding; however, it cannot be scaled down to represent individual understanding (Henry 2010).

5.2 Standardizing Concepts or Free Association of Concepts?

Related to the choice of FCM collection is the question of whether to construct FCMs using standardized concepts or freely associated concepts. The standardization of concepts involves providing participants with the same list of predefined concepts from which to construct their individual FCMs (Gray et al. in press). On the other hand, FCM elicitation through free association of concepts allows individuals to populate FCMs with their own freely chosen concepts (Özesmi and Özesmi 2004; Gray et al. 2012a). The standardization method facilitates knowledge combination via aggregation of individuals' maps by eliminating the need for the researcher to subjectively categorize and reduce the large quantity of concepts typically resulting from FCM elicitation using free association. However, while easing the task of model aggregation and reducing the role of the researcher in determining the concept aggregation scheme, time investment in stakeholder discussions and preliminary research is still required to define an appropriate list of standardized concepts. Additionally, when model concepts are standardized, accumulation curves cannot be used to determine the appropriate sample size of individuals (Özesmi and Özesmi 2004). Further, although standardizing model structures facilitates the ease of scenario modeling with aggregated maps, the reliability of model structure and function may be biased since predefined concepts shape individuals' cognitive abstractions (Rouse and Morris 1985; Pohl 2004). Therefore, variation in knowledge perceived by individuals with high degrees of knowledge heterogeneity may not be captured. To mitigate some of these challenges in the group contexts with standardized concepts, it is recommended that researchers attempt to reduce knowledge variability and increase reliability of knowledge contributions by attempting to homogenize expertise by the type of experts constructing maps. These homogenized expertise maps can then be integrated with other groups maps after they are collected. It is important to note, however, that homogenized expertise also has trade-offs associated with it since map construction with overlapping expertise may limit the application of FCM as a tool for facilitating multi-person, multi-objective decision making in diverse group settings. In more heterogeneous expert contexts, freely associated concepts provide obvious advantages; however, this freedom has the ability to overwhelm individuals, especially if they are non-traditional experts, or if FCM or concept mapping is not a familiar activity.

Despite the notion that standardized concepts pose some analytical constraints, some research benefits are provided in terms of measuring shared knowledge. For example, in a group context, the use of standardized concepts may scaffold participants and promote social learning as a result of the group discussion and through the model validation process. Additionally, there are also considerations of ease of collection that should be considered in the selection of FCM collection techniques. While the research objective should be the first criteria used to inform FCM collection, availability of funding, and/or staff and participant time availability often influence the choice of data collection as well. When resources are limited, standardized concepts offer many benefits by facilitating the collection of larger sample sizes, which can be useful in drawing conclusions about the knowledge of communities and take less time to elicit as well as to aggregate. In the group context, they can also save time which may permit real time revision, and therefore create a more useful discussion of structural agreement. In contrast, FCM collection using freely associated concepts can require increased time dedicated to FCM elicitation, aggregation, analysis and follow-up validation.

While there are variations on FCM collection options, careful consideration of the research goals as well as the community and expert context should be undertaken so that methodological limitations are diminished to the greatest extent possible. Obviously, hybrid methods that combine pre-selected components and freely associated concepts are also possible, and to some extent can mitigate drawbacks associated with both options.

Conclusions:

Structuring human knowledge through the collection of FCMs has obvious utility beyond simply characterizing traditional expert systems, and also provides a way to represent community understanding as a form of scaled up "mental modeling". As the field of FCM continues to evolve and the utility of FCM continues to be seen through novel appropriations, continued research is needed to establish best practice standards which match specific techniques with different research contexts, backed by discipline appropriate theoretical foundations. Although FCM provide a powerful tool for both traditional experts and non-traditional experts to model complex systems, evaluate structural differences between the knowledge held by groups and individuals, and functionally determine the dynamic outcome of this understanding, there are still issues regarding the interpretation of FCMs as artifacts of individual knowledge and group beliefs. In this chapter, we have sought to provide a theoretical background to inform the collection and interpretation of FCM as representations of shared knowledge when individual FCMs are aggregated together, compared across individuals within the context of group interaction, or created collectively by individuals within a group context. More specifically, we can summarize the lessons learned as follows:

- When FCMs are used as representations of individual mental models or group knowledge or beliefs, the research objective should be carefully aligned with the appropriate cognitive theory and collection method.

- FCMs, like all concept maps, have the ability to be used as both measurements of individual and group understanding and as a tool to promote social learning to facilitate group decision-making. Researchers should be clear about their appropriation when drawing conclusions about FCM as representation of knowledge and beliefs.

- Researchers engaged in FCM research should justify, based on tradeoffs, the selection of FCM data collection and aggregation techniques.

- Continued evaluation of existing methods, and the development of new methods, is currently needed in the areas of aggregation tests, sample size sufficiency, knowledge heterogeneity, and expert credibility.

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