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INTRODUCTION

Systems science is a discipline dealing with sets of systems of ‘organized complexity’. Systems science originated from the experimental sciences, general systems theory and cybernetics, and it has evolved into a distinct area for the development of systems theory to explain the structure and behavior of various systems (Flood and Carson, 1988; Schoderbek et al., 1975). Systems science focuses on the developmental processes of systems thinking, theory and application and include various specialized frameworks such as general systems theory and various particularized systems theories like systems analysis,
The essence of the systems approach is explained by Ackoff:

A system is a whole that cannot be taken apart without loss of its essential characteristics, and hence it must be studied as a whole. Now, instead of explaining a whole in terms of its parts, parts began to be explained in terms of the whole. Therefore, things to be explained are viewed as parts of larger wholes rather than as wholes to be taken apart . . . Thus, Systems Science is not a science, but science taken as a whole and applied to the study of wholes. (Foreword by Russell L. Ackoff in Schoderbek et al., 1975, p. viii)

The systems approach to organization and management has been an important application area of systems science to real-world systems and aims at better understanding the organization as a system and at predicting future states of the organization through model building. The importance of understanding and applying the systems approach to organization and management is described by Schoderbek et al. (1975), p.X: ‘Perhaps systems thinking has had its greatest impact in the area of human organization . . . Familiarity with the systems approach has become a condicio sine qua non for understanding modern management thinking.’ This is true for the management information systems (MIS) area which is a part of the management systems. Nonetheless, the contributions of systems science/systems approach to the development and evolution of MIS have not been well recognized in the information systems literature, except for recent studies of Eom (1996a) and Xu (1992, 1995).

This study aims at examining the contributions of the systems science/systems approach to the development of each of the DSS research sub-specialty areas by means of an empirical assessment of the DSS literature and traces how concepts and findings by systems science researchers have been picked up by DSS researchers to be applied, extended and refined in the development of DSS research subspecialties. Studying the reference disciplines improves DSS research as researchers adopt their theories as well as assess what these theories imply for DSS research. Defining the reference disciplines is also a way of introducing quality control since information systems research grounded in coherent reference disciplines is less likely to issue a new contingency theory/framework (Keen, 1980).

Despite the field’s short history of less than 30 years, the study of Eom provides hard evidence that the decision support systems area has made meaningful progress over the past two decades and is in the process of solidifying its domain — six major areas of DSS research (group DSS, foundations, model management, user interfaces, multicriteria DSS and implementation) and demarcating its reference disciplines (multiple-criteria decision-making, cognitive science, organizational science, artificial intelligence and systems science). Especially, much progress has been made in the subareas of model management such as model representation, model base processing, model integration and artificial intelligence application to model management leading towards the development of a theory of models.

DATA

A database file was created consisting of a total of 23,768 cited reference records taken from the 944 citing articles in the DSS area over the past 23 years (1971–1993). Of these 944 articles, 472 are collected from the following sources: 210 articles from Elam et al. (1986); 157 articles from Sprague and Watson (1989); 203 articles from Eom and Lee (1990). The additional 472 articles are included to cover the period the three sources did not cover, taken from the same source journals and selected using the same selection criteria used by the three source articles. For a detailed description of the database file, see Eom (1995, 1996a).

RESEARCH METHODOLOGY

This study uses author cocitation analysis (ACA). ACA is a technique of bibliometrics that applies
quantitative methods to various media of communication such as books, journals, conference proceedings and so on. Citation analysis is often used to determine the most influential scholars, publications or universities in a particular discipline by counting the frequency of citations received by individual units of analysis (authors, publications, etc.) over a period of time from a particular set of citing documents. However, citation analysis cannot establish relationships among units of analysis. ACA is the principal bibliometric tool to establish relationships among authors in an academic field and thus can identify subspecialties of a field and how closely each subgroup is related to each of the other subgroups.

The cocitation of authors occurs when a citing paper cites any work of authors in reference lists. The cocitation frequency of authors represents relationships between authors. Authors whose works are cited together frequently are interpreted as having close relationships between them. ACA is based on the assumptions that ‘cocitation is a measure of the perceived similarity, conceptual linkage, or cognitive relationship between two cocited items (documents or authors)’ and ‘cocitation studies of specialties and fields yield valid representations of intellectual structure’ (McCain, 1986, p. 111). It should be noted that the term ‘author’ refers to a body of writings by a person, not the person himself/herself (McCain, 1990).

It is critical to establish a diversified list of authors. If the chosen authors do not represent the full range of variability in subject specializations, methodologies/reference disciplines, the intellectual structure of a field and the interrelationships among its research subspecialties and its contributing disciplines cannot be found (McCain, 1990). The final author set of 113 was chosen by applying the overall cocitation frequency over 25 with himself/herself (see Eom, 1996a, for a list of 113 authors included in the study and see McCain 1990, p. 435, for a detailed discussion of several different approaches to compiling a list of authors). To overcome a standard problem with the Institute for Scientific Information (ISI) database search method which codes only the first author of a cited work, a FoxBASE-based cocitation matrix generation system was developed to compute a cocitation frequency between any pair of authors. The cocitation matrix generation system gives access to cited co-authors as well as first authors. The raw cocitation matrix of 113 authors is converted to the correlation coefficient matrix by the %DISTANCE macro (updated on June 28, 1994) of the SAS/STAT sample library of the SAS Institute, Inc. An example of raw cocitation matrix can be found in Appendix A of Eom (1995). The SAS data set, converted from the raw cocitation matrix, is analyzed by the principal component analysis with the latent root criterion (eigenvalue 1 criterion) applied to obtain the solution of 11 factors as reported in Eom (1996a). The correlation coefficient matrix is analyzed by the cluster analysis program of SAS (a hierarchical agglomerative clustering program with Ward’s trace option). Cluster analysis is a multivariate data analysis technique whose primary purpose is to group variables into homogeneous subgroups on the basis of their similarities or dissimilarities (Kaufman and Rousseeuw, 1990). In the agglomerative methods, each variable starts out as its own cluster. In each subsequent step, the two closest clusters are combined into a new, bigger cluster. This build-up process continues until all variables are combined into one final cluster that contains all variables in the data set.

EMPIRICAL INVESTIGATIONS OF THE RELATIONSHIP BETWEEN THE DSS SUBSPECIALTIES AND SYSTEMS SCIENCE

This study extends a previous study of Eom (1996a). In that study, factor analysis of the DSS literature extracted 11 factors. The 11 factors extracted consist of six major areas of DSS research (group DSS, foundations, user interfaces, model management, multicriteria DSS and implementation) and five contributing disciplines (systems science, multiple-criteria decision-making, cognitive science, artificial intelligence and organizational science). The PROMAX rotation specification generated a table of interfactor correlations among the 11 factors that emerged (Table 1). The PROMAX rotation method is one
of several methods used in extracting factors in the factor procedure. This PROMAX specification provides both orthogonal and oblique rotations with only one invocation of PROC FACTOR (SAS, 1988). This table provides an avenue for assessing the degree of diffusion of ideas/concepts among DSS research subfields and various DSS contributing disciplines. However, this interfactor correlation table cannot provide us with a detailed understanding of how each subgroup is internally aligned (internal homogeneity within-cluster) and how closely each subgroup is related to each of the other subgroups (external heterogeneity between clusters) (Hair et al., 1987). For that reason, this research applied CLUSTER procedure (a hierarchical agglomerative clustering program with Ward’s trace option). Cluster analysis uncovered 12 clusters consisting of six major areas of DSS research (group DSS, foundations, model management, user interfaces, multicriteria/negotiation DSS and implementation) and six contributing disciplines (multiple-criteria decision-making, cognitive science, organization science, artificial intelligence, group decision-making and systems science).

The cluster analysis resulted in a dendrogram (tree graph), which illustrates hierarchical clustering (Figure 1). The dendrogram provides us with a detailed understanding of how closely each subgroup is related to each of the other subgroups. The dendrogram may be compared to a family tree displaying whole family members and their proximity to each other. The sooner two subfields join, from top to bottom, the more similar the subfields are.

It should be emphasized that proper interpretation of relationships between the DSS subspecialties and reference disciplines needs to simultaneously examine the factor structure (the correlations of the variables with the factors) and the interfactor correlations. Especially, interfactor correlations (Table 1) provide us with an avenue for assessing the degree of diffusion of ideas from the reference disciplines to the DSS research subfield and the interdependency among factors. Figure 1 provides us with a detailed understanding of how closely each subgroup of DSS research subspecialties/contributing disciplines is related to each of the other subgroups. The bold area highlights the interdependence between the systems science factor and all other factors.

Table 1. Interfactor correlations

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Factor 1 Group Decision Systems.
Factor 2 Foundations.
Factor 3 User Interfaces.
Factor 4 Model Management.
Factor 5 Multicriteria Decision Making.
Factor 6 Cognitive Science.
Factor 7 Artificial Intelligence.
Factor 8 Organizational Science.
Factor 9 Systems Science.
Factor 10 Multicriteria DSS.
Factor 11 Implementation.
Before we empirically investigate the contributions of systems science to the development of DSS subspecialties, let us begin to present a big picture of the DSS area. As Figure 2 shows, an empirical investigation of the DSS literature over the past two and a half decades concludes that the intellectual structure of DSS research is built heavily on the architecture of specific DSS, termed the Dialog–Data–Models Paradigm, by Sprague and Carlson (1982), and the organizational perspectives of Keen and Scott Morton (1978) emphasizing the design, development, implementation and evaluation of decision support systems (Eom, 1966b).

The study of DSS consists of the following research areas:

1. Developing a decision support system (labeled ‘A’ in Figure 2). Over the past two decades, about 200 hundred specific functional DSS applications have been developed and published (Eom and Lee, 1990) (labeled ‘B’).

Table 2. The relationships among factor, cluster and labels

<table>
<thead>
<tr>
<th>Factor</th>
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</tr>
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<td>26</td>
<td>I</td>
<td>User Interfaces</td>
</tr>
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<td>4</td>
<td>20</td>
<td>H</td>
<td>Model Management</td>
</tr>
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<td>5</td>
<td>24</td>
<td>J4</td>
<td>Multiple-Criteria Decision-Making</td>
</tr>
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<td>6</td>
<td>15</td>
<td>J2</td>
<td>Cognitive Science</td>
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<td>36</td>
<td>J1</td>
<td>Artificial Intelligence</td>
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<td>8</td>
<td>86</td>
<td>J5</td>
<td>Organizational Science</td>
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<td>9</td>
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<td>J6</td>
<td>Systems Science</td>
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<td>12</td>
<td>H</td>
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<tr>
<td>11</td>
<td>13</td>
<td>D</td>
<td>Implementation</td>
</tr>
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</table>
(2) Developing DSS theory:

(A) Developing theory for each component of the Dialog–Data–Models Paradigm (labeled ‘F’–‘I’). Although the paradigm did not explicitly include the user (the decision-maker), the user is an essential component of the Sprague and Carlson architecture.

(B) Developing theory on design and development, implementation and evaluation of Keen and Scott Morton’s framework (labeled ‘C’, ‘D’ and ‘E’).

(C) Study of reference disciplines (Labeled ‘J’). As depicted in Figures 1 and 2, there are five major reference disciplines that have influenced the development of five DSS research subfields of implementation, user interface, model management, foundations, and multicriteria DSS. Cluster 86 (factor 8) represents Organization Science (labeled ‘J5’). Organization science is concerned with the behavior, attitude and performance of individuals, groups, and organizations within an organizational setting. Organization scientists have classified organizational decision-making in terms of several schools of thought: (i) the rational model (Mintzberg, 1973; Mintzberg et al., 1976) focusing on the selection of the most efficient alternatives, with the assumption of a rational, completely informed, economic man; (ii) the organizational process model (Cyert and March, 1963) stressing the compartmentalization of the various units in any organization; (iii) the satisficing model (March and Simon, 1958; Simon, 1976), based on the theory of intended and bounded rationality, emphasizing the behavior of human beings who satisfice due to their inability to perform/make correct decisions; (iv) and other models. Readers are referred to Eom and Farris (1996) for a comprehensive review of the contributions of organizational science to the development of DSS subspecialties.

Cluster 15 (factor 6) represents Cognitive Science (labeled ‘J2’). The central component of cognitive science is the study of the human adult’s normal, typical cognitive activities such as language understanding, thinking, visual cognition and action by drawing on a...
number of disciplines such as linguistics, artificial intelligence, philosophy, cognitive psychology, neuroscience and cognitive anthropology. The focus of cognitive science research is on how cognition typically works in normal adults, how it varies across individuals/populations/cultures, how it develops, how it is realized in the brain, etc. (Von Eckardt, 1993).

Cluster 36 (factor 7) represents Artificial Intelligence (labeled ‘J1’). According to Winston (1992, p. 5), ‘Artificial intelligence is the study of the computations that make it possible to perceive, reason, and act.’ The field has two central goals: making computers more useful and understanding the principles that make intelligence possible. The basic ideas include useful problem-solving procedures (description matching and goal reduction), exploring alternatives, studying control metaphors such as general problem solver, and representing common sense knowledge, language understanding, image understanding, etc.

Cluster 24 (factor 5) represents Multiple-Criteria Decision-Making (labeled ‘J4’). Multiple-criteria decision-making (MCDM) deals with a general class of problems that involve multiple attributes, objectives and goals (Zeleny, 1982). By the nature of MCDM, usually there are numerous non-dominated solutions in MCDM problems. To single out a decision alternative, Geoffrion et al. (1972) suggested interactive procedures for multiple-criteria optimization. To deal with decisions with conflicting objectives, DSS may include an array of diverse MCDM algorithms/techniques such as ordinal comparisons (Geoffrion et al., 1972), pairwise alternative comparisons (Zionts and Wallenius, 1976), implicit utility functions (Keeney and Raiffa, 1976), and many others (Jackson and Keys, 1984; Xu, 1988).

Cluster 25 (factor 9), Systems Science (labeled ‘J6’), represents a contributing discipline dealing with the set of systems of ‘organized complexity’. In the following sections, the contributions of systems science/systems approach will be examined.

The Contributions of Systems Science to DSS Foundations

Foundations of DSS are primarily concerned with providing definitions, architectures and taxonomies of DSS. Most founding fathers of DSS areas, including Keen and Scott Morton, have provided definitions and architectures (a set of filing cabinets with many drawers). Drawing on various definitions that have been suggested (Alter, 1980; Bonczek et al., 1981; Keen and Scott Morton, 1978; Sprague and Carlson, 1982), a DSS is described as a computer-based interactive system that

- supports decision-makers rather than replaces them;
- utilizes data and models;
- solves problems with varying degrees of structure — non-structured (unstructured or ill-structured) (Bonczek et al., 1981); semi-structured (Bennett, 1983; Keen and Scott Morton, 1978); and semi-structured and un-structured tasks (Sprague and Carlson, 1982); and
- focuses on the effectiveness rather than the efficiency of decision processes (facilitating decision processes).

Four sets of filing cabinets (of design, development, implementation and evaluation of DSS from an organizational perspective) were provided by Keen and Scott Morton (1978). Sprague and Carlson (1982) added several important cabinets of data, model, dialogue and decision-makers, which can be termed a DSS architecture. In addition, Sprague and Carlson (1982) examined the necessity of including decision models in an integrated MIS and emphasized that there is a need for a systematic way of embedding decision support models into MIS to support managers’ decision-making processes. They created another cabinet that stores the important and widely accepted definitions and concepts of specific decision support systems, DSS tools and DSS generators.

In the early stage of DSS development, systems scientists provided an essential concept for defining the concept of decision support systems and justifying the need for such systems in
organizations. Ackoff (1967) clearly pinpointed a need for another type of business computing systems, decision support systems, to relieve managers' suffering from an 'over abundance of irrelevant information' and classified systems according to their different behavior into state-maintaining, goal-seeking, purposive and purposeful. Ackoff (1971, p.670) also defined organization as a purposeful system that contains at least two purposeful elements which have a common purpose relative to which the system has a functional division of labor; its functionality distinct subsets can respond to each other's behavior through observations or communication; and at least one subset has a system control function.

A review of the definitions of the DSS shows divergent opinions on the varying degree of decision structures that a DSS is directed toward. Nevertheless, all of these definitions agree that the DSS must support decision-makers in solving unprogrammed and unstructured problems. Unstructured problems are usually associated with potentially conflicting objectives (Bennett, 1983; Stabell, 1979), uncertain decision environments (Bennett, 1983; Stabell, 1979) and complex variable structure (Holloway, 1979; Simon, 1960). Defining an unstructured task is essential to understanding the concept of DSS. Unfortunately, there is no universal definition of an unstructured task. According to Simon (1960, p.6), an unstructured decision is made in a situation where there is no 'cut-and-dried method for handling the problem because it hasn’t arisen before, or because its precise nature and structure are elusive and complex, or because it is so important that it deserves custom-tailored treatment'. If we adopt Simon's definition of unstructured tasks, the complexity of decision structure is an important factor that distinguishes unstructured decisions from structured ones.

Flood (1987) gives us an erudite discussion of complexity and presents a transportable conceptual framework (see also, Klir, 1985; Warfield, 1976, 1994; and Warfield and Cárdenas, 1994; for excellent discussions of system complexity). The concept of complexity is disassembled by two factors: systems and people. Furthermore, complexity is related to systems via a number of elements and relationships, and to people via their notions/perceptions, interests and capabilities. For a detailed discussion, see Flood, 1987; Flood and Carson, 1988). The essence of Flood's framework is that 'Systems are objects as perceived by people'. Using a similar analogy, complex decisions (as a subsystem of complex systems) are perceived as such by decision-maker(s). The objects can be organizational or personal problems. Although Flood (1987) did not explicitly include attributes of an element in his model as a factor that increases the complexity, he indirectly recognizes the importance of the attributes of an element by describing a (problem) situation as 'an assembly of elements related in an organized whole'. The assembly of elements is complicated by a relationship between two (or more) elements and the number of attributes of those elements (Flood and Carson, 1988, p.7).

In addition, there are numerous discussions on uncertain decision environments (Flood and Carson, 1988) and multiple, often conflicting, goals (Jackson and Keys, 1984). For example, 'Towards a system of systems methodologies' (Jackson and Keys, 1984) classifies problems into four different types: (1) mechanical-unitary; (2) systemic–unitary; (3) mechanical–pluralist; and (4) systemic–pluralist sets. Clearly, unstructured, complex managerial problems can be classified as systemic–pluralist sets. In dealing with the systemic–pluralist type of problems, Jackson and Keys (1984) maintain that the principal task of the manager and management scientist is to learn how to remove or resolve any conflicts between different goals (see also Keys, 1988). Holloway (1979, p.5) emphasizes another aspect of the complexity of problems by stating that 'there are four factors that can make a problem complex enough to make some form of analysis attractive: (1) a large number of factors, (2) more than one decision maker, (3) multiple attributes, (4) uncertainty'. If one or more of these characteristics is present, the problems become complex. Of course, complex decisions are not always unstructured decisions.
Lee and Eom (1990) further refined the dis-assembly of complexity suggested by Flood and presented a more detailed framework based on the various models discussed (Bennett, 1983; Flood, 1987; Flood and Carson, 1988; Holloway, 1979; Jackson and Keys, 1984; Simon, 1960; Stabell, 1979). Their framework systematically conceptualizes several sources of complex, unstructured tasks and shows that multiple attributes and objectives have been important sources of complex, unstructured decision-making.

Since a DSS is defined as a computer-based interactive system that solves problems with varying degrees of structure, formulating/identifying problem has been recognized as a critical element of the modeling process (Intelligence Stage). Adopting the systems concept of Ackoff (1971), Courtney and Paradise (1993, p. 413) defined the problem formulation as ‘the process of deciding what variables are included in a problem domain and how those variables fit together and interact’.

In the next stage of problem-solving (Design Stage), Brightman (1978) contends that, depending on the level in the organization in which the ill-structured problem occurs, different problem-solving processes as well as different intellectual skills and tools may be necessary. Strategic problems at the strategic management level are usually associated with a high degree of uncertainty and complexity, whereas operating problems at the lower management level are not. Solving strategic problems demands intuition and judgement of the decision-makers as well as effective tools such as decision support systems that can aid the decision-maker in designing/generating alternatives and choosing the best alternative. General systems theory provides a useful principle in solving strategic and operating problems. Negative feedback is the solution principle to manage a first-order feedback system to deal with operating problems. Negative feedback is usually associated with self-regulation and minimizing deviations between set standards and actual performance (Schoderbek et al., 1975). On the other hand, principles of memory, search and recall are paramount in solving strategic problems. This is the case of second-order feedback systems that can ‘initiate alternative courses of action in response to changed external conditions and can choose the best alternative for the particular set of conditions’ (Schoderbek et al., 1975, p. 72). Cybernetics has played an important role in designing management information and decision support systems. The essence of cybernetics is concerned with feedback as a means of controlling the closed-loop feedback systems.

In the DSS design area (label ‘C’), DSS researchers have developed several development methodologies such as a decision-centered approach (Gerrity, 1971), an organizational change process approach (Keen and Scott Morton, 1978), the ROMC (representations, operations, memory aids and control aids) approach (Sprague and Carlson, 1982), and a system-oriented approach (Ariav and Ginzberg, 1985). Readers are referred to Arinze (1992) for a comprehensive review of DSS development methodologies.

Ariav and Ginzberg (1985) contend that a large number of DSS design studies have emphasized a single set of related issues such as the nature of decision situations, components, tools and technologies of DSS, the processes of DSS design and use, etc. They strongly believe that a systemic view of DSS can provide a unified approach to effective design of DSS and can serve as a basis for accumulating DSS research results. The fundamental system properties outlined by Churchman (1968) are as follows: (1) objectives of the total system: the problem is defined and the objective of the system must be viewed in relation to the other components and to larger systems/the whole system; (2) the systems environment; (3) the resources of the system; (4) the components of the system: a system is composed of interrelated elements and the design of a system is the design of subsystems and their relationships; and (5) the management of the system.

Churchman (1971) presented the theory of designing inquiring systems, which discussed a set of necessary conditions for conceiving a system. The set of conditions provides the system designer with a set of precepts for building an integral system. Churchman’s theory of inquiring systems was further elaborated by Kinston
Ariav and Ginzberg (1985) applied his theory of design integrity to designing effective DSS. They asserted that to develop a solid basis for design DSS researchers and designers must have a systemic view of DSS — understanding the DSS system elements, selecting the necessary system elements from an understanding of the environment and objectives of the DSS (its intended impact on its environment), and that effective DSS design must explicitly consider a common set of DSS elements (DSS environment, DSS components and resources) simultaneously and their interaction, strongly reflecting Churchman’s view that ‘all systems are design non-separable’ (1971, p. 62). The DSS framework of Ariav and Ginzberg (1985) is applied to present a systemic description of the various components and capabilities of DSS and to analyze the potential contribution of artificial neural networks for decision support as well as some intrinsic constraints that might inhibit their use (Schocken and Ariav, 1994). Te’eni and Ginzberg (1991) also questioned the adequacy of existing DSS methodology such as the linguistic approach (prototyping approach), the ROMC approach and the decision research approach. To quote Te’eni and Ginzberg (1991, pp. 127–128):

In each of these approaches, it is assumed that the decision context can be defined, a decision support system appropriate to that context can be built. The DSS is the product of that development process, and once implemented will play an invariant role in the decision process. We contend that this is too narrow a view of DSS and that the systems approach to the DSS should begin at one higher level; that is, it should start with the analysis of the decision system. A decision system includes a DSS and a decision maker (DM), both of which can be viewed as resources in the decision process. The decision system needs to allocate these resources dynamically according to the changing conditions of the decision situation.

This broad definition of DSS roles led them to present a new framework for developing DSS that recognizes new functions that can be incorporated in future DSS designs. They named this kind of DSS ‘flexible’ DSS as it promotes use, creativity, exploratory learning and adaptability. Attempts are being made to apply Churchman’s theory of designing inquiring systems to collaborative, human–computer problem solving to enhance creativity. In the 1992 DSS prize-winning paper, Angehrn (1993) introduced the conversational framework for decision support, which was a new and promising direction for developing future generations of DSS. According to Angehrn, this conversational framework is the basis of a new generation of active and intelligent decision support systems and executive information systems. The active DSS will be equipped with the tool (stimulus agents) that will act as experts, servants or mentors to decide when and how to provide advice and criticism to the user, while the user formulates and inquires about its problems under the continuous stimulus of electronic agents.

Systems theory is also being applied to build executive information systems (EIS) theory. Walls et al. (1992) presented a design theory of vigilant information systems to provide rigorous and valid guidance to effective EIS design. Other application areas of the systems approach include information systems planning. Based on the work of Hegel and Singer, Churchman (1971) suggested a methodology called ‘dialectical design’ that examines a situation completely and logically from two different points of view. Two of Churchman’s disciples, Mason and Mitroff, further extended Churchman’s ideas into a rigorous methodology (strategic assumption surfacing and testing) for uncovering (surfacing), analyzing the effect and challenging key policy assumptions in dealing with ill-structured problems (Mason and Mitroff, 1981). Kottemann and Konsynski (1984) and McIntyre et al. (1986) described knowledge-based techniques using semantic inheritance networks for view integration and for providing a flexible and automated model of information systems planning via integrating three perspectives: external, internal and procedural. This planning approach (Kottemann and Konsynski, 1984; McIntyre et al., 1986) is identical to the application of systems approach by Mason and Mitroff (1981).
The Contributions of Systems Science on Implementation (Label 'D')

Managers have increasingly criticized computer professionals for their relative inability to deliver systems that meet users' real needs and that are on time and cost-effective. They point to innumerable instances of models and systems being built but never used. The reasons for this failure in implementation seem rarely to be technical. The systems 'work' but are either little value to managers or awkward to use in regular operations. (Keen and Scott Morton 1978, p. 189)

Cluster 13 (factor 11) appears to represent Implementation. A central theme of DSS implementation research includes the investigation of DSS system implementation failures. Research in the DSS implementation area has attempted to systematically identify the implementation success/failure factors and the relationship between user-related factors (cognitive style, personality, demographics and user-situational variables) and implementation success (Alavi and Joachimsthaler, 1992).

A strong intercorrelation among the systems science cluster (cluster 25), implementation cluster (cluster 13) and user interfaces cluster (cluster 26) is attributable to the work of Churchman, who has been a systems scientist, management scientist and implementation researcher. As a systems scientist, Churchman laid out a matrix that explains the types of confrontation between the manager and the scientist, which may cause the implementation problem (Churchman and Schainblatt, 1965). The implementation matrix was further extended by Huysmans (1970) and Doktor and Hamilton (1973) to conclude that the cognitive styles of users/managers did affect the chances of implementation. Subsequently, the majority of researchers on DSS implementation have expanded the implementation success factors to include other user-related factors such as personality, demographics and user-situational variables, in addition to cognitive styles, and have focused on the empirical examination of the relationship between the user-related factor and implementation success (Alavi and Joachimsthaler, 1992). A meta-analysis of 144 findings concluded that user-situational variables (involvement, training and experience) are more important than the other variables such as cognitive style, personality and demographics (Alavi and Joachimsthaler, 1992).

Ginzberg (1981) contends that many DSS implementation failures are caused by emphasizing only technical aspects of the system and not paying enough attention to behavioral and organizational impacts within an organization. In other words, he believes a closed systems approach taken by the previous development approaches is a direct cause of DSS system failures. Subsequently, many researchers suggested a systems approach to the development of DSS. Ahn and Grudnitski (1985) proposed a conceptual model of DSS development, based on an open systems approach which emphasizes and does take into account various technical, behavioral and organizational factors in DSS development, built on the concept of closed and open systems (Ackoff, 1971) — 'A closed system is one that has no environment. An open system is one that has. Thus a closed system is one which is conceptualized so that it has no interaction with any element in it'. The problem should be defined and the objective of the system must be viewed in relation to the other components and to larger systems/the whole system (Churchman, 1971).

The Contributions of Systems Science to Individual Difference/User Interface (Label 'I')

The user interfaces (dialogue) component is a subsystem of a decision support system, along with the data, model and user subsystems. Sprague and Carlson (1982, p. 198) define the dialogue component as 'the software and hardware that provide the user interface for a DSS'. Specifically, 'the dialog component presents the DSS outputs to the users and collects the user inputs to the DSS' by performing the following functions:

(1) produces the output representations;
(2) enables user inputs that invoke and provide parameters for the operations;
(3) enables user inputs that invoke and provide parameters for the memory aids;
(4) provides the control mechanisms that enable the user to combine outputs and inputs into processes (dialogs).

Cluster 26 (factor 3) seems to represent User Interfaces. Over the last two decades (the 1970s and 1980s), a great deal of information systems research was motivated by the belief that the user’s cognitive style should be considered an important factor in the design of MIS/DSS and that decisions seem to be a function of the decision-maker’s cognitive make-up, which differs for different psychological types. Researchers in this area focused on (1) useful classification of behavioral variables for attaining successful MIS/DSS design and (2) consideration of the system user’s cognitive style/psychological type in the design and implementation of the successful information system (Huber, 1983; Mason and Mitroff, 1973; Zmud, 1979) and (3) the evaluation of graphical and color-enhanced information presentation and other presentation formats such as tabular (Dickson et al., 1977). Despite the numerous previous research reports, results are inconclusive. To extend the previous line of research on the effectiveness of different presentation modes (e.g., graphical vs. tabular), Te’eni (1989) investigated the usefulness of employing an intermediate variable, perceived complexity, to examine the impact of two information systems (IS) variables (the mode of presentation and the number of windows) on performances of users. Unlike many previous studies of mode of presentation, his study introduced a new variable: the use of multiple windows within a single application. He concludes that ‘the use of windows seems to be significantly more important for tabular, rather than graphical, presentation. The consideration of other interactions between IS characteristics, and their contingency on the decision setting, is therefore important in research and practice’. The conclusions of Te’eni are drawn with the help of many previous research results of neighboring disciplines such as cognitive science and systems science concerning the environmental/perceived complexity associated with tasks and their effects on performance. Van Gigch (1978) contributed to our understanding of complexity in a system. According to Van Gigch, the ‘objective complexity’ in a system is a product of the mental load and the rate of repetition of a given task.

The focus of the research on user interfaces appears to have shifted from the individual differences/cognitive style perspective of the last two decades to the development of user interface management systems for building the human–computer interface which will be both useful and easy to use by employing graphical direct-manipulation interfaces (Rathnam and Mannino, 1995), and graph-based modeling using graph grammars (Jones, 1995).

The Contributions of Systems Science on Model Management (Label ‘H’)

Model management (model base management systems) allows the user the capability to analyze problems. A model base is a library of models. The model base consists of management science/operations research models, statistical models, financial models, etc. The model base management system is a software that permits the user to build, update, store and operate models.

Cluster 20 (factor 4) represents Model Management. Since 1975, model management has been researched to encompass several central topics such as model base structure and representation, model base processing, and application of artificial intelligence to model integration, construction and interpretation (Blanning, 1993). Further, model management is concerned with the ongoing management of models as organizational resources in order to avoid wasteful duplication, excessive costs and inconsistent decisions (Muhanna, 1994). Readers are referred to Blanning (1993), Chang et al. (1993), Dolk and Konsynski (1984), Dolk and Kottemann (1993) and Geoffrion (1987), for comprehensive literature reviews on model management.

An important research area in model management includes the sharing, reuse and integration of models to construct models from reusable ones stored in a repository. Kim et al. (1990)
implemented system entity structure, which is a structural knowledge representation scheme containing knowledge of decomposition, taxonomy and coupling of a system. The system entity structure construct provides a foundation for model base management through managing a sharable repository of models in simulation environments and assists users to combine models from reusable components to solve semi-structured problems. The system entity structure-based model base management system is attributable to systems theory (Zadeh and Desoer, 1963) of decomposition (i.e., breakdown of a system into subsystems to departmentalize relationships) and coupling (i.e., linking of a system’s elements to construct a relationship).

Muhanna and Pick (1994) successfully implemented a prototype model management system designed to support model sharing, reuse and integration. The prototype system of Muhanna is built on the systems concept. Their essential framework for model management views models as systems, which ‘allows powerful systems concept and structuring principles to be brought to bear on the problems of Model Management’. Their prototype model management system has the following distinctive characteristics (Muhanna and Pick, 1994, p.1100):

The systems framework supports (1) model-solvers independence — the separation of model specification (model schema) from implementation (solver); (2) model–data independence — the separation of a model schema from sets of data values that instantiate schema variables and coefficients; and (3) the division of a model schema specification into external (interface) specification comprising what we call a model type and internal (structural and behavioral) specification which constitute what shall be called a model version.

Vepsalainen (1988) proposed a relational approach for modeling organizations. The relational view of organizational activities for DSS design and analysis shifts emphasis to the problem finding, structuring, and information requirements analysis in early intelligence stages, from the problem analysis in the design stages.

Etymologically, the relational view is derived from the systems approach of Churchman (1968) and socio-cybernetics (Geyer and Van der Zouwen, 1978). Vepsalainen (1988, p.209) described the kernel of the approach: ‘Activities and their interaction are represented, at an appropriate level of detail, as diagonal activity matrices. The visual modeling and data collection for further analysis can be started before actual problems have been identified and without preconceived ideas of the eventual activity citing’.

The Contributions of Systems Science on GDSS (Label 'F')

Single-user DSS and group decision support systems (GDSS) can be distinguished in many different ways in terms of purpose and components (hardware, software, people and procedures). DeSanctis and Gallupe (1985, p.3) define a group DSS as ‘an interactive computer-based system which facilitates solutions of unstructured problems by a set of decision-makers working together as a group’. Readers are directed to Benbasat et al. (1993), Dennis and Gallupe (1993), Dennis et al. (1988) and Pinsonneault and Kraemer (1989) for comprehensive reviews of major GDSS research.

Two contributing disciplines (systems science and group decision-making) are identified as reference disciplines of GDSS (DeSanctis and Gallupe, 1987; Gallupe et al., 1988; Kraemer and King, 1988; Nunamaker et al., 1991; Steeb and Johnston, 1981; Turoff and Hiltz, 1982; Watson et al., 1988; Stefik et al., 1987). In addition, two other contributing disciplines (organization science and human communication) were discussed in the GDSS literature (DeSanctis, 1993; Nunamaker et al., 1989). Of these, coordination theory by the human communication school of thought has been proposed as a guiding set of principles for development and evaluation of GDSS. The coordination theory concerns the analysis of different kinds of dependencies among activities and the identification and management of the coordination processes (Malone and Crowston, 1994). Research in the interdisciplinary study of coordination is grounded
in several disciplines such as computer science, organization science, management science, economics, psychology and systems science. General systems theory in particular (Churchman, 1968, 1971) provides cybernetic models of the interplay between computers, group members, goals, etc. Turoff et al. (1993) contend that the essence of GDSS is to support a communication and coordination process and in supporting this process, methodologies and techniques which are rooted in many contributing disciplines such as systems science and group decision-making were adopted as fundamental tools. For example, earlier works by Delbecq et al. (1975) experimentally compared three alternative methods for group decision-making: the conventional interacting (discussion) group, the nominal group technique and the Delphi technique. Many of these techniques (silent and independent idea generation, presenting each idea in a round-robin procedure, silent independent voting, etc.) were successfully utilized in the development of GDSS in the 1980s.

According to Nunamaker et al. (1989), systems science is one of several fundamental reference disciplines that serve as a useful framework for defining and explaining the foundational components from which GDSS can progress soundly. For example, a GDSS is defined as a set of elements (human and machine components) working together to accomplish objectives and as an open system interacting with the environment and adjusting to the changing circumstances. The soft systems methodology (SSM) of Checkland (1981) was cited as a useful framework for GDSS concepts (Nunamaker et al., 1989, p. 141):

Checkland’s Soft Systems Methodology (SSM) recognizes the ambiguities inherent in dealing with human interface issues while preserving the concepts of decomposition, coupling and cohesion that are essential to the development and evaluation of Group Support Systems, in which adaptation and evolution are ways of life.

In the systems science literature, there are two basic methodologies to deal with ill-structured problem: hard systems methodology and soft systems methodology. Hard systems methodology is concerned with selecting an efficient means of achieving a known and defined end (e.g., systems analysis, systems engineering, operations research/management science). On the other hand, the SSM of Checkland (1981, 1989) can be best applied to the ill-structured problems in which boundaries and objectives are often difficult to define.

The systems approach is also applied to the development of automated support for stakeholder identification and assumption surfacing. Based on the work of Hegel and Singer, Churchman (1971) suggested a methodology called ‘dialectical design’ by examining a situation completely and logically from two different points of view. Mason and Mitroff (1981) further extended Churchman’s ideas into a rigorous methodology (assumption analysis) for uncovering (surfacing), analyzing the effect, and challenging key policy assumptions in dealing with ill-structured problems.

CONCLUSION

This research has elucidated the intellectual bases of DSS research through the identification of the reference disciplines and their contributions on the development of DSS research subspecialties, with a particular emphasis on assessing the contributions of systems science to the development of foundations, design and development, implementation, model management, user interfaces and group DSS. This research is the first formal comprehensive recognition and analysis of the contributions of systems science/systems approach to the development of DSS research subspecialties. In 1980, Peter Keen (1980, p. 18) states, ‘Building a rich, meaningful field of study involves more than just “doing” research … There is a need for reflection on the field, its roots, relations with other disciplines and historical context’.

Studying the reference disciplines improves DSS research as researchers adopt their theories as well as assess what these theories imply for DSS research. Defining the reference disciplines
is a way of introducing quality control since information systems research grounded in coherent reference disciplines is less likely to issue a new contingency theory/framework (Keen, 1980). Reference disciplines are referential for the researchers in an immature field. One important role of the reference disciplines is to provide us with good research methods and ideas.

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