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Theory and Methodology

Relationships between the decision support system subspecialties and reference disciplines: An empirical investigation

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Abstract

This is a comprehensive study, that, by means of an empirical assessment of the DSS literature, systematically identifies the DSS reference disciplines and traces how concepts and findings by researchers in the contributing disciplines have been picked up by DSS researchers to be applied, extended, and refined in the development of DSS research subspecialties. Cluster analysis was employed to an author cocitation frequency matrix derived from a comprehensive database of the DSS literature over the period of 1970 through 1993. Twelve clusters were uncovered consisting of six major areas of DSS research (group DSS, foundations, model management, user interfaces, implementation, and multiple criteria DSS) and six contributing disciplines (multiple criteria decision making, cognitive science, organization science, artificial intelligence, group decision making, and systems science). © 1998 Elsevier Science B.V.

Keywords: Decision support systems; Intellectual structure; Reference disciplines; Bibliometrics; Cluster analysis; Cocitation analysis

1. Introduction

Since the term "decision support systems" (DSS) was coined in the early 1970s, a growing number of studies in the area of DSS over the past two and a half decades has been reported [e.g., [31,34,36,39]]. The growing body of DSS research reflects the DSS community's struggle to establish a substantive and coherent field of study. In 1980, Peter Keen identified and discussed three main necessary conditions for the field of management information systems to become a coherent research field [53]. They were (1) clarification of reference disciplines, (2) definition of the dependent variable, and (3) building a cumulative tradition. These three conditions are necessary for DSS research as well. What are the reference disciplines for DSS? Have we built a cumulative DSS research tradition? What is the dependent variable in DSS research? The DSS area has many *assumed* references such as micro-economic theory, cognitive psychology, applied psychology, behavioral decision theory, computer science, information theory, information economics, political and administrative sciences, human factors and ergonomics, management science, etc. [71]. Studying the reference disciplines

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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 [53].

The present work is conducted to infer the intellectual structure of the DSS field by means of an empirical assessment of the DSS literature. This study focuses on examining the structure of DSS research with a particular emphasis on assessing the contributions of reference disciplines to the development of each of the DSS subspecialty areas. This study builds on two previous studies [36,39] and traces how concepts and findings by researchers in the contributing disciplines have been picked up by DSS researchers to be applied, extended, and refined in the development of DSS researchsubspecialties. In the previous study [39], principal component analysis with the latent root criterion (eigenvalue 1 criterion) is applied to obtain eleven factors. The eleven extracted factors account for 84.97 percent of the total variances of the data set.

The eleven factors extracted consist of six major areas of DSS research — factor 1 (group DSS), factor 2 (foundations), factor 3 (user interfaces), factor 4 (model management), factor 10 (multi-criteria DSS), and factor 11 (Implementation) and five contributing disciplines — factor 5 (multiple criteria decision making), factor 6 (cognitive science), factor 7 (artificial intelligence), factor 8 (organizational science), and factor 9 (systems science). Readers are referred to [39] for in-depth discussions in regard to implications and directions for future DSS research as well as list of publications (84 articles and 26 books) receiving 15 or more citations by co-citing factors.

2. Data

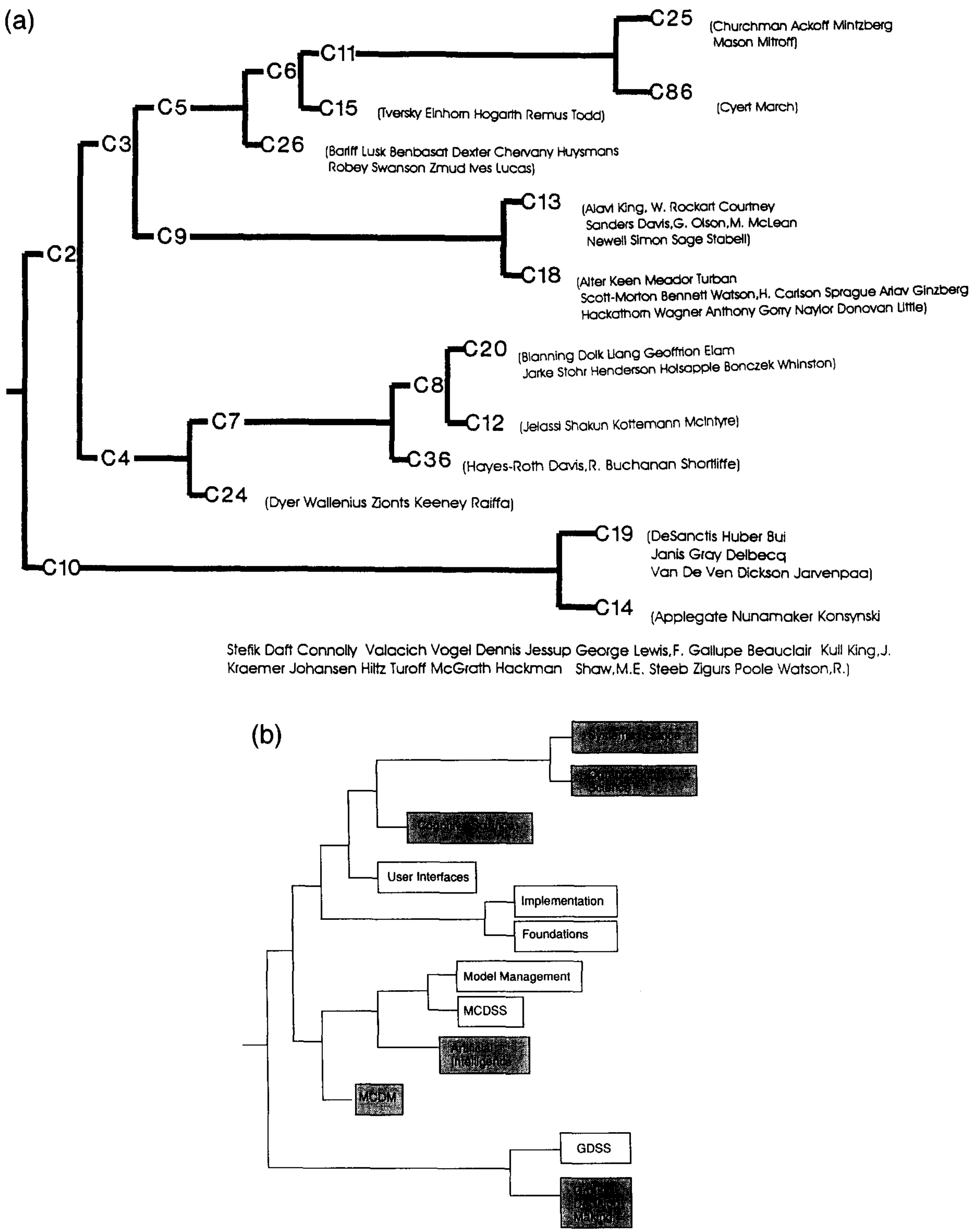
A database file was created consisting of a total of 23 768 *cited* reference records taken from the 944 *citing* articles in the DSS area over the past 23 years (1971–1993). Of these 944 articles, 472 are collected from the following sources: 210 articles from [31]; 157 articles from [81]; 203 articles from [34]. 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 [36,39].

3. 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" [[64], p. 111]. It should be noted that the term "author" refers to a body of writings by a person, not the person himself/herself [65].

Fig. 1. a. The dendogram depicting DSS research areas and contributing disciplines. b. Dendogram illustrating the relationship between the DSS subspecialties and reference disciplines.


(a)
C2
C3
C5
C6
C11
C25
(Churchman Ackoff Mintzberg
Mason Mitroff)
C86
(Cyert March)
C15
(Tversky Einhorn Hogarth Remus Todd)
C26
(Bariff Lusk Benbasat Dexter Chervany Huysmans
Robey Swanson Zmud Ives Lucas)
C9
C13
(Alavi King, W. Rockart Courtney
Sanders Davis,G. Olson,M. McLean
Newell Simon Sage Stabell)
C18
(Alter Keen Meador Turban
Scott-Morton Bennett Watson,H. Carlson Sprague Ariav Ginzberg
Hackathorn Wagner Anthony Gorry Naylor Donovan Little)
C4
C7
C8
C20
(Blanning Dolk Liang Geoffrion Elam
Jarke Stohr Henderson Holsapple Bonczek Whinston)
C12
(Jelassi Shakun Kottemann McIntyre)
C36
(Hayes-Roth Davis,R. Buchanan Shortliffe)
C24
(Dyer Wallenius Zionts Keeney Raiffa)
C10
C19
(DeSanctis Huber Bui
Janis Gray Delbecq
Van De Ven Dickson Jarvenpaa)
C14
(Applegate Nunamaker Konsynski
Stefik Daft Connolly Valacich Vogel Dennis Jessup George Lewis,F. Gallupe Beauclair Kull King,J.
Kraemer Johansen Hiltz Turoff McGrath Hackman Shaw,M.E. Steeb Zigurs Poole Watson,R.)
(b)
User Interfaces
Implementation
Foundations
Model Management
MCDSS
Artificial Intelligence
MCDM
GDSS

The final author set of 113 was chosen by applying the overall cocitation frequency over 25 with himself/herself. (See [[65], p. 435] for a detailed discussion on 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 coauthors 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. 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 [51]. 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.

4. Empirical investigations of the relationship between the DSS subspecialties and reference disciplines

Cluster analysis uncovered twelve clusters consisting of six major areas of DSS research (group DSS, foundations, model management, user interfaces, multiple criteria/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 (Fig. 1). The dendrogram provides us with a detailed understanding of how each subgroup is internally aligned (internal homogeneity within cluster) and

Table 1
Interfactor correlations indicating the strength of the interconnection between the factors

Factor	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	−0.11	1									
3	0.07	0.45	1								
4	0.06	0.49	0.11	1							
5	−0.08	0.21	−0.00	0.25	1						
6	0.06	0.19	0.31	0.30	0.16	1					
7	−0.05	0.47	0.06	0.55	0.14	0.24	1				
8	0.09	0.39	0.30	0.15	0.21	0.17	0.14	1			
9	0.17	0.32	0.30	0.18	0.13	0.22	0.10	0.46	1		
10	0.21	0.24	−0.01	0.37	0.29	0.12	0.27	−0.04	−0.05	1	
11	0.12	0.42	0.42	0.23	0.05	0.13	0.09	0.39	0.35	0.14	1

Factor 1 Group decision support systems.
Factor 2 Foundations.
Factor 3 Used interfaces.
Factor 4 Model management.
Factor 5 Multiple criteria decision making.
Factor 6 Cognitive science.
Factor 7 Artificial intelligence.
Factor 8 Organization science.
Factor 9 Systems science.
Factor 10 Multiple criteria DSS
Factor 11 Implementation.

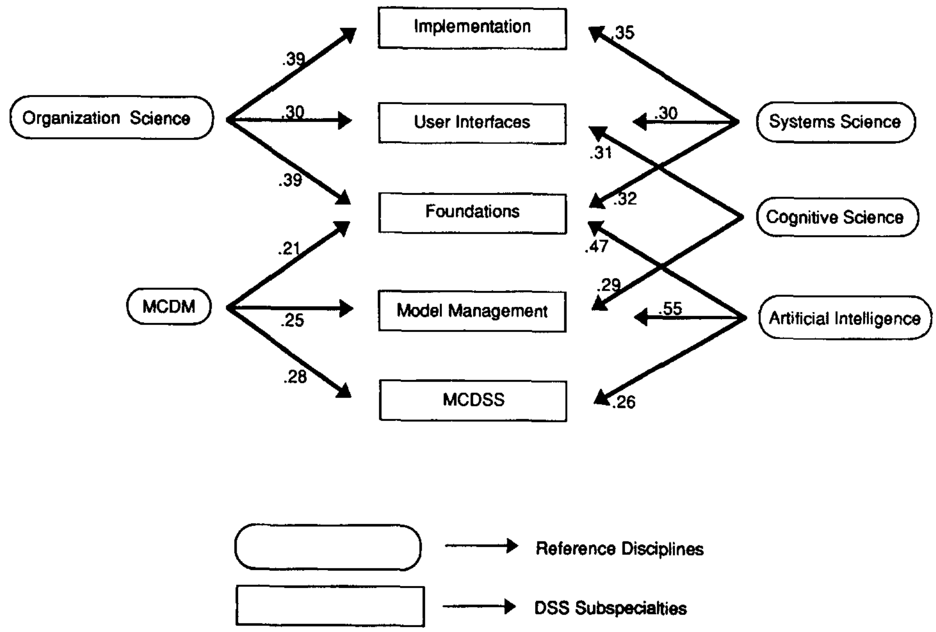


Fig. 2. Major factor intercorrelation networks.

how closely each subgroup is related to each of the other subgroups (external heterogeneity between clusters) [43]. 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.

Making an analogy between the field of DSS and a tree, the tree graph shows that DSS can be compared to a tree where GDSS is grafted onto the main stem. The grafted tree has five branches (user interfaces, model management, multiple criteria decision support systems (MCDSS)/Negotiation support systems, foundations, and implementation) from the main stem and a GDSS branch grown from the bud inserted into the stem.

In addition to cluster analysis, it should be emphasized that proper interpretation of relationships between the DSS subspecialties and reference disciplines needs to examine the factor structure (the correlations of the variables with the factors) and the inter-factor correlations. Especially, inter-factor correlations provides 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. Table 1 and Fig. 2 are by-products of the previous study [39]. Fig. 2 depicts major factor intercorrelation networks at the correlation level ≥ 0.2. For example, the foundations of DSS research have been influenced by four contributing disciplines: multiple criteria decision making, artificial intelligence, organization science, and systems science.

5. The impact of systems science on user interfaces and implementation

The discussion of the diffusion of ideas from the reference disciplines to the DSS subspecialties follows the sequential order (left to right) of the appearance of reference disciplines in the dendrogram, beginning from systems science and ending with group decision making.

Cluster 25, *Systems Science*, represents a contributing discipline dealing with the set 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. Systems science focuses on the developmental processes of systems thinking, theory, and application. Systems approach is the application of systems theory and systems thinking 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 core concept of the systems approach includes the following: 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* [14].

Cluster 26 (factor 3) semms 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 as an important factor in the design of MIS/DSS and that decisions seem to be a function of the decision maker's cognitive makeup, 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 [45,62,89] and (3) the evaluation of graphical and color enhanced information presentation and other presentation formats [25]. Despite the numerous previous research reports, results are inconclusive [23].

Cluster 13 (Factor 11) appears to represent *Implementation*. Research in the DSS implementation area has attempted to systematically identify the implementation success factors and the relationship between user-related factors (cognitive style, personality, demographics, and user-situational variables) and implementation success [1].

A strong intercorrelation among the systems science cluster (cluster 25), implementation cluster (cluster 13), and user interfaces cluster (cluster 26) is attributable to the works 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 [15]. The implementation matrix was further extended by Huysmans [46] and Doktor and Hamilton [26] to conclude that the cognitive styles of users/managers did affect the chances of implementation. Subsequently, the majority of researchers on DSS implementation research have expanded the implementation success factors to include other user-related factors such as personality, demographics, and usersituational variables, in addition to cognitive styles, and have focused on the empirical examination of the relationship between the user-related factor and implementation success [1].

6. The impact of systems science on foundations

Churchman presented the theory of designing inquiring systems [13], 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. Ariav and Ginzberg [3] applied his theory of design integrity to designing effective DSS. They asserted that effective DSS design must explicitly consider a common set of DSS elements simultaneously including DSS environment, task characteristics, access pattern, DSS roles and function, and DSS components, strongly reflecting Churchman's view that "all systems are design nonseparable" [[13], p. 62]. Attempts are being made to apply his theory of designing inquiring systems to collaborative, human-computer problem solving to enhance creativity. This is a new and promising DSS research direction as suggested by Angehrn [2].

Other application areas of the systems approach include information systems planning. Based on the work of Hegel and Singer, Churchman [13] 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 [63]. Kottemann and Konsynski [56] and McIntyre, Konsynski, and Nunamaker [67] 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 [56,67] is identical to the application of systems approach by Mason and Mitroff [63].

7. The impact of organization science on foundations

Cluster 86 (Factor 8) represents *Organization science*. 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: 1) the rational model [69,70] focusing on the selection of the most efficient alternatives, with the assumption of a rational, completely informed, economic man; 2) the organizational process model [17] stressing the compartmentalization of the various units in any organization; 3) the satisficing model [61,79], 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; 4) and other models.

DSS are designed and implemented to support organizational as well as individual decision making. Organization scientists [17,70] provided the foundational concepts on which DSS design is based. Keen and Scott Morton [52] stated: "A main argument of the DSS approach is that effective design depends on the technician's detailed understanding of management decision processes...." They further outlined the design strategy of the descriptive-normative comparison: the design of DSS requires identification of both the normative decision process that the system is intended to generate and the actual decision process that exists [52].

8. The impact of organization science on user interfaces and implementation

Simon [79] pointed out that for the individual to be equipped to make the correct decisions, the organization must place him in a psychological environment that will adapt his decisions to the organization's objectives and that will provide the individual with the information needed to make decisions correctly.

Mason and Mitroff [[62], p.478] extended the works of Simon [79] and hypothesized that "the designers of information systems should not force all psychological types to conform to one type of information system, rather each psychological type should be given the kind of information to which he is psychologically attuned and uses most effectively." The seminal work of Mason and Mitroff [62] propelled the emergence of the individual differences research subspecialty in MIS/DSS, which had persisted for nearly two decades during the 1970s and 1980s.

9. The impact of cognitive science on user interfaces and implementation

Cluster 15 (factor 6) represents *Cognitive Science*. 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/different populations/cultures, how it develops, how it is realized in the brain, etc. [85].

A theory of problem solving by Simon and Newell [72] sheds some light on understanding of how intelligent adults solve short (half-hour), moderately difficult problems of a symbolic nature such as those in chess, symbolic logic, and algebra-like puzzles. The study of human cognitive limitation has been another important area of cognitive science. Tversky and Kahneman [83] described an aspect of human cognitive limitation — cognitive biases that arise from the reliance on judgmental heuristics. They showed that people rely on several heuristic principles in making judgements under uncertainty (representativeness, availability of instances, and adjustment from an anchor), which are usually effective, but lead to systematic and predictable errors. Einhorn and Hogarth [30] reviewed behavioral decision theory to place it within a broad psychological context. In so doing they emphasized the importance of attention, memory, cognitive representation, conflict, learning, feedback to elucidate the basic psychological processes underlying judgment, and choice. They concluded that decision makers use different decision processes for different tasks. The decision processes are sensitive to seemingly minor changes in the task-related factors.

Some of the contributions of cognitive scientists to user interfaces and implementation research include the following:

1. A foundational framework was presented to recognize many of the dimensions along which the total human system can vary (e.g., tasks, time scale, phylogenetic scale), although their theory was not concerned with personality variables (individual differences).
2. The organization of the problem representation significantly influences the structure of the problem space and the problem-solving processes decision makers use. Therefore, when their problemsolving processes are adapted to the problem representation, decision makers make effective decisions, and this will lead to successful implementation of DSS.
3. The limitations of the human information processing system (relatively slow serial processor with small short-term memory [72] and the cognitive biases [83]) contributed to the development of the ROMC (Representation, Operations, Memory Aids, and Control Mechanisms) approach to the user interface design [80]. The ROMC approach emphasizes that a focus for DSS design is to provide users with familiar representations (graphs, plots, maps, charts, etc.) in order to communicate some aspect of the decision to other persons and that several types of memory aids should be provided to extend the users' limited memory.
4. The findings of cognitive scientists provided a theoretical basis for developing a theory to explain the role and performance of graphs and tables in decision making [84] and led to an important conclusion that the cognitive styles of users should not be the basis of information systems design since "predispositions are often dysfunctional" [45].

10. The impact of cognitive science on model management

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 [7]. In the model base structure and representation area, the structured modeling approach by Geoffrion [41] has advanced the model representation area of model management, which is an extension of the entity-relationship data model and a necessary step for advancing to the next stage of model management (model manipulation). In the model processing area, Blanning [6] investigated important issues in the design of relational model bases and presented a framework for the development of a relational algebra for the specification of join implementation in model bases. Dolk and Konsynski [27,190] developed the model abstraction structure for representing models as a feasible basis for developing model management systems. Readers are referred to [7,12,28] for comprehensive literature reviews on model management.

A group of DSS researchers are continuing to build DSS to support the problem structuring phase [58], which is the first stage of the decision making process (intelligence [problem formulation], design, and choice). In this line of research toward building an interactive graphics-based problem-structuring aid such as the Graphical Interactive Structural Modeling Option (GISMO), important contributions have been made by cognitive psychology [30,83], imagery theory, dual coding theory, structured modeling, and a theory of problem solving [72] in investigating the relationship between the effectiveness of problem-structuring and an individual's general thinking skills. Using GISMO, Loy [58] found that the user's ability to create and use visual images is positively related to better problem-solving and problem-structuring performance. His findings imply that further DSS research is necessary to develop DSS tools which can provide effective support for decision makers who do not possess highly developed visual thinking skills.

11. The impact of artificial intelligence on model management

Cluster 36 (factor 7) represents Artificial Intelligence (AI). According to Winston [[86], 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; representing common sense knowledge, language understanding, image understanding, etc.

AI, as depicted in Figs. 1 and 2, has influenced the development of model management, foundations, and multiple criteria DSS. In the area of AI application to model management, the concept of knowledge-based model management systems was introduced to support tasks of formulating a new decision model and/or choosing an existing model from the model base, analyzing the model, and interpreting the model's result [32,33]. Other researchers suggested the use of artificial techniques (predicate calculus) for determining how models and data should be integrated in response to a user query [6,9]. Dutta and Basu [29] presented an artificial intelligence approach to machine representation of models and development of mechanical methods for automatic selection, synthesis, and sequencing of models to generate query responses within the framework of first-order logic. Dolk and Kottemann [28] attempt to connect both artificial intelligence and database management systems to evolve a theory of model management via model integration that relies heavily upon the relational database theory. They believe that the emergence of a theory of model management is imminent. See [33] for thorough review of the application of AI to enhance the capabilities of model management systems.

12. The impact of artificial intelligence on foundations

The linkage between the foundations cluster (cluster 18 and factor 2) and the AI factor can be found in the creation of knowledge-based DSS. The DSS architecture of Bonczek, Holsapple, and Whinston [8] presented a substantially new approach toward decision support, that is, the integration of AI, linguistics, and database management systems. Applying the generalized state-space representation and means-ends analysis of the problem-solving process, they viewed DSS as systems that utilize state-space analysis and that consist of knowledge systems, language systems, and problem processing systems [8]. Turban and Watkins [82] examined possible connections between AI and DSS and discussed some issues related to their integration to build knowledge-based systems which provide users with the intelligence in structuring a decision, selecting models, and interpreting the output. To help ameliorate human cognitive limitations [83], expert decision support systems have been proposed by many DSS researchers [76]. Successful expert systems such as the MYCIN system [18] have been extensively examined to illustrate the concept of knowledge engineering for building business applications of ES.

Since then, AI has been an important contributing discipline for building knowledge based systems for organizational decision making. A recent survey [38] revealed that few business areas remain untouched by AI. ESs have apparently made the transition from the research laboratory to the commercial market. ES developers have been integrating ESs with other technologies such as barcode scanning systems, programming languages, case-based reasoning systems, natural language processing systems, robots, DSS, image processing systems, and artificial-neural-networks. These tools that combine ESs with other artificial intelligence techniques generate synergistic effects to shrink the time for tasks from days to hours, minutes, or seconds.

13. The impact of artificial intelligence on MCDSS

Cluster 12 (Factor 10), *Multiple criteria DSS/ Negotiation Support Systems* represents MCDM model-embedded decision support systems [10,35, 48,49]. They can be broadly categorized into a generalized data-oriented MCDSS which is based on multiattribute decision making models [49], a model-oriented MCDSS which is based on multiple objective decision making models [35], and data-oriented MCDM Group DSS [10] and negotiation support systems [48].

Some efforts have been made to integrate various AI techniques into the MCDSS to develop the knowledge-based or "intelligent" MCDSS. The knowledge-based MCDSS may guide and provide reasoning about the appropriateness of the MCDM model formulation (structuring a decision), exploration/construction of the alternative set (based on the generalized state-space representation and means-ends analysis [86]), evaluation of the alternatives/criteria, construction of the utility functions, and interpretation of outputs [40].

An example of operational intelligent MCDSS is reported to overcome the gap between the knowledge of DMs and the difficulty of using MCDSS [57]. Moreover, an artificial neural network system is developed to solve discrete MCDM problems via formulating and assessing the utility function by eliciting information from the DMs and ranking and rating alternatives. The system does not assume any particular structure of the utility functions [59].

14. The impact of MCDM on foundations

Cluster 24 (Factor 5) represents *Multiple criteria Decision Making (MCDM)*. MCDM deals with a general class of problems that involve multiple attributes, objectives, and goals [87]. Among numerous individuals whose contributions have given rise to the field of MCDM, Keeney and Raiffa [54] developed the theory and methods of quantifying preferences over multiple objectives to help an individual decision maker structure multiple objective problems, and make a choice among a set of prespecified alternatives. By the nature of multiple criteria decision making, usually there are numerous nondominated solutions in MCDM problems. To single out a decision alternative, Geoffrion, Dyer, and Feinberg [42] 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 [42], pairwise alternative comparisons [88], implicit utility functions [54], and many others [49]. A brief review of a problem oriented multiple criteria decision making research up to 1992 can be found in [55].

A critical link between works of the founders of DSS and multiple criteria decision making (MCDM) lies in the basic definition and concepts of DSS. Keen and Scott Morton [52] suggested a widely accepted definition of DSS which implies "the use of computers to: assist managers in their decision processes in semistructured tasks." A task is unstructured when its objectives are ambiguous and nonoperational, or its objectives are relatively operational but numerous and conflicting [5]. Zeleny [[87], p. 74] challenges the reader with the following statement: "No decision making occurs unless at least two criteria are present. If only one criterion exists, mere measurement and search suffice for making a choice."

15. The impact of MCDM on MCDSS

Integration of MCDM into DSS has long been advocated by the researchers in both areas. Keen and Scott Morton [[52], p.48] believe that the multiple criteria decision problem is at the core of decision support and "A marriage between MCDM and DSS promises to be practically and intellectually fruitful." The emergence of MCDM model-based DSS was predicted in the early 1980s [87]. A series of studies [35,38,39] reached the compelling conclusion that the MCDM model-embedded DSS have positioned themselves at the core of DSS. An important reason for the emergence of MCDSS is that MCDM complements DSS and vice versa due to the differences in underlying philosophies, objectives, support mechanisms, and relative support roles [71]. MCDSS intend to provide the necessary computerized assistance to decision makers (DMs) in such a way that the following desirable goals are met [[68], p. 405]:

1. Both descriptive solution aids (those isomorphic with DMs have been observed to solve the problems) and normative solution models (i.e., formal models and/or algorithms) are available.

2. The DM is encouraged to explore the support tools available in an iterative fashion with the aim of further defining and refining the nature of the problem.

The ultimate success of DSS lies in its ability to help decision makers solve ill-structured problems through direct interaction with analytical models. Such an ability can be enhanced by intermingling the various features of MCDM with DSS. These features include (1) the multiple-objective goal structure designed to handle quantitative and qualitative information crucial for ill-structured problems, (2) the interactive solution search procedure designed to analyze continuous trade-offs among various alternatives until the best available solution is attained, and (3) the emphasis on the decision maker's judgment or bounded rationality which better reflects his/her actual cognitive behaviors.

16. The impact of MCDM on model management

The interactive capability of many MCDM models has significantly contributed to the successful implementation of DSS in practical situations. The interactive versions of MCDM models (e.g., interactive multi-objective linear programming and interactive goal programming) have increased the DSS model's flexibility for sensitivity testing and/or goal seeking through dynamic changes in aspiration levels. Integration of the MCDM models into the model base has strengthened their interactive capability to assist the decision maker in testing "what-if" scenarios via continuous data and model updates. Especially, the graphical information display mechanics in MCDM models (e.g., signal flow graphs, Andres' harmonic curves, Chernoffs' faces, etc.) can provide the user with a powerful interface tool which enhances a dialogue between the model and the user. (For a detailed discussion of this topic, see [40].)

Should model management in single-user DSS be different from the one for multiperson-user DSS? This line of inquiry was pursued by Bui and Jarke [48,11]. According to Bui and Jarke [11], multi-person DSS should have different functional capabilities due to the needs of communication among multi-person decision makers and the need for negotiation among persons as well as through their DSS. Each decision maker may want to consult multiple models/knowledge bases/databases. They contend that the model management in multi-person DSS requires strong communications components to support knowledge sharing and negotiation support for consensus-seeking and compromise. MCDM method was implemented as protocols for communication and negotiation in the prototype multi-user DSS, Co-oP, for multiple criteria multiperson decision making [11].

17. The impact of group decision making and other reference disciplines on GDSS

Although we identified only two contributing disciplines (systems science and group decision making) as reference disciplines of GDSS, all contributing reference disciplines for GDSS research are hidden in cluster 14. Comprehensive reviews of major GDSS research can be found in [3,21,22,74]. In addition, two other contributing disciplines (organization science and human communication) were discussed in the GDSS literature [24,73].

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 [60]. Research in the interdisplinary 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 [13,14] provides cybernetic models of the interplay between computers, group members, goals, etc.

Researchers in the area of behavioral decision making also have made an essential contribution to the design and development of GDSS. Shaw [78] indicated that groups reach more and better solutions to problems than do individuals. Issues related to group think have been discussed by Janis [47]. A series of experiments by McGrath [66] concluded that "individuals brainstorming alone and later pooling produce more ideas, of a quality at least as high, as do the same number of people brainstorming in a group'' due to several possible reasons such as evaluation apprehension, free riding, and production blocking. Several experiments of GDSS researchers with an idea generation support system, electronic brainstorming (EBS), produced a result which contradicts that of face-to-face group brainstorming. Groups using the EBS system generated more ideas than did the same number of individuals brainstorming on their own and later pooling outputs [16].

Earlier works by Delbecq, Van de Ven, and Gustafson [19] 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 1980's.

18. Conclusion

This research has elucidated the intellectual bases of DSS research through the identification of the reference disciplines and their impact on the development of DSS research subspecialties. This paper examined the following two of the three issues addressed by Peter Keen [53]: What are the reference disciplines for DSS? Have we built a cumulative DSS research tradition? DSS research subspecialties and contributing disciplines uncovered by this research imply that a cumulative research tradition has emerged in DSS research and the DSS area is in the process of solidifying its domain and demarcating its reference disciplines. The third issue raised by Keen concerning the dependent variable in DSS research was fortunately addressed by DeLone and McLean [20]. They introduced a comprehensive taxonomy which posits six dimensions of information systems success measures (the dependent variables) [20]. Consequently, the necessary conditions for decision support systems to become a classical and coherent discipline appear to have been met.

Although the DSS community has made meaningful progress over the past two and a half decades toward solidifying its domain and to demarcating its reference disciplines, many challenges await us. The boundaries of the DSS area can be shaped by the development of its own well-grounded theories for supporting practitioners in the integrated process of design, implementation, and evaluation of decision support systems. This research points to several positive signs that imply that we have made significant progress toward the development of DSS theories that can be applied in practice to improve individual, group, and organizational performance. Numerous seemingly conflicting results of empirical research are now being (or have been) reinterpreted/ reviewed to organize a confusing body of research into a coherent whole through the use of cumulative research techniques such as meta-analysis, cumulative experimental approach, etc. For example, a theory of cognitive fit has been presented [84] to explain the role and performance of graphs and tables — a longstanding controversy [23]. We are adjusting the focus of our attention from the enumeration of the factors influencing implementation success to the effective management of important factors. 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 [1]. Consequently, the intellectual structure of DSS research is changing. Since 1990, individual difference research has been fading away [37]. 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 [75], graph-based modeling using graph-grammars [50]. Furthermore, there have been intensifying research efforts in DSS implementation and increasing adoption of theories/techniques from cognitive science and AI [37].

As Keen [53], 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.'' This research focused on identifying the roots of DSS research and investigating the relationship between the DSS subspecialties and the reference disciplines to provide a groundwork for future scientific inquiry and aims to facilitate the development of articulated theory in the field.

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