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Past, present, and future of decision support technology [☆]

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Abstract

Since the early 1970s, decision support systems (DSS) technology and applications have evolved significantly. Many technological and organizational developments have exerted an impact on this evolution. DSS once utilized more limited database, modeling, and user interface functionality, but technological innovations have enabled far more powerful DSS functionality. DSS once supported individual decision-makers, but later DSS technologies were applied to workgroups or teams, especially virtual teams. The advent of the Web has enabled inter-organizational decision support systems, and has given rise to numerous new applications of existing technology as well as many new decision support technologies themselves. It seems likely that mobile tools, mobile e-services, and wireless Internet protocols will mark the next major set of developments in DSS. This paper discusses the evolution of DSS technologies and issues related to DSS definition, application, and impact. It then presents four powerful decision support tools, including data warehouses, OLAP, data mining, and Web-based DSS. Issues in the field of collaborative support systems and virtual teams are presented. This paper also describes the state of the art of optimization-based decision support and active decision support for the next millennium. Finally, some implications for the future of the field are discussed. © 2002 Published by Elsevier Science B.V.

Keywords: Decision support technology; DSS development; Collaborative support systems; Virtual teams; Optimization-based decision support

1. Introduction

Decision support systems (DSS) are computer technology solutions that can be used to support complex

decision making and problem solving. DSS have evolved from two main areas of research—the theoretical studies of organizational decision making (Simon, Cyert, March, and others) conducted at the Carnegie Institute of Technology during the late 1950s and early 1960s and the technical work (Gerrity, Ness, and others) carried out at MIT in the 1960s [32]. Classic DSS tool design is comprised of components for (i) sophisticated database management capabilities with access to internal and external data, information, and knowledge, (ii) powerful modeling functions accessed by a model management system, and (iii) powerful, yet simple user interface designs that enable interac-

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43 tive queries, reporting, and graphing functions. Much
44 research and practical design effort has been conducted
45 in each of these domains.

46 DSS have evolved significantly since their early
47 development in the 1970s. Over the past three dec-
48 ades, DSS have taken on both a narrower or broader
49 definition, while other systems have emerged to assist
50 specific types of decision-makers faced with specific
51 kinds of problems. Research in this area has typically
52 focused on how information technology can improve
53 the *efficiency* with which a user makes a decision, and
54 can improve the *effectiveness* of that decision [49].

55 The evolution of information technology infrastruc-
56 tures parallel the three eras of growth in the computer
57 industry—the data processing (DP) era, the micro-
58 computer era, and the network era [44]. Based on the
59 infrastructures, DSS tools started in the DOS and UNIX
60 environments around the late 1970s and then moved to
61 Windows in the early 1990s. The advent of the Internet
62 has given rise to many new applications of existing tech-
63 nology. The technology behind DSS is well suited to
64 take advantage of the opportunities that the World Wide
65 Web (Web) presents, especially the rapid dissemination
66 of information to decision-makers. The Web's impact
67 on decision making has been to make the process more
68 efficient and more widely used. This is due largely to
69 the fact that a typical browser serves as the user inter-
70 face component of the decision-making systems, i.e.,
71 making the technology easy to understand and use.

72 The evolution of the human–computer interface is
73 the evolution of computing. The graphical user inter-
74 face (GUI) that was refined at Xerox, popularized by
75 Macintosh, and later incorporated into Windows, and
76 then the Palm, are typical examples of how significant
77 the GUI is integrating technology into decision-mak-
78 er's and/or user's daily tasks. In the future, decision-
79 makers will access electronic services through their
80 mobile phones or other wireless devices as much as
81 through their desktop computers. In the future, mobile
82 tools, mobile e-services, and wireless Internet proto-
83 cols will mark the next major sets of development in
84 DSS [15], thereby expanding the accessibility of the
85 tools to decision-makers wherever they may be.

86 The primary purpose of this paper is to present the
87 past, present, and future of decision support systems,
88 including the latest advances in decision support tools.
89 The paper discusses a number of important topics
90 including development of the DSS concept, data ware-

housing, on-line analytical processing, data mining, 91
Web-based DSS, collaborative support systems, virtual 92
teams, knowledge management, optimization-based 93
DSS, and active decision support for the next millen- 94
nium. This paper has seven main sections. The next 95
section discusses development of the DSS concept. 96
Section 3 is a description of data warehousing, on-line 97
analytical processing, and data mining. Section 4 dis- 98
cusses collaborative support systems, virtual teams, 99
and knowledge management. Section 5 discusses opti- 100
mization-based DSS, and Section 6 discusses active 101
decision support for the next millennium. The final 102
section provides some implications for the future of 103
decision support technology. 104

2. Development of the DSS concept 105

The original DSS concept was most clearly defined 106
by Gorry and Scott Morton [23], who integrated 107
Anthony's [2] categories of management activity and 108
Simon's [54] description of decision types. Anthony 109
described management activities as consisting of stra- 110
tegic planning (executive decisions regarding overall 111
mission and goals), management control (middle man- 112
agement guiding the organization to goals), and opera- 113
tional control (first line supervisors directing specific 114
tasks). Simon described decision problems as existing 115
on a continuum from programmed (routine, repetitive, 116
well structured, easily solved) to nonprogrammed 117
(new, novel, ill-structured, difficult to solve). Gorry 118
and Scott Morton combined Anthony's management 119
activities and Simon's description of decisions, using 120
the terms structured, unstructured, and semi-structured, 121
rather than programmed and nonprogrammed. They 122
also used Simon's Intelligence, Design, and Choice 123
description of the decision-making process. In this 124
framework, *intelligence* is comprised of the search for 125
problems, *design* involves the development of alter- 126
natives, and *choice* consists of analyzing the alterna- 127
tives and choosing one for implementation. A DSS was 128
defined as a computer system that dealt with a problem 129
where at least some stage was semi-structured or un- 130
structured. A computer system could be developed to 131
deal with the structured portion of a DSS problem, but 132
the judgment of the decision-maker was brought to bear 133
on the unstructured part, hence constituting a human– 134
machine, problem-solving system. 135

136 Gorry and Scott Morton also argued that character-
 137 istics of both information needs and models differ in a
 138 DSS environment. The ill-defined nature of informa-
 139 tion needs in DSS situations leads to the requirement
 140 for different kinds of database systems than those for
 141 operational environments. Relational databases and
 142 flexible query languages are needed. Similarly, the
 143 ill-structured nature of the decision process implied
 144 the need for flexible modeling environments, such as
 145 those in spreadsheet packages.

146 Fig. 1 describes what probably came to be a more
 147 customarily used model of the decision-making pro-
 148 cess in a DSS environment. Here, the emphasis came to
 149 be on model development and problem analysis. Once
 150 the problem is recognized, it is defined in terms that
 151 facilitate the creation of models. Alternative solutions
 152 are created, and models are then developed to analyze
 153 the various alternatives. The choice is then made and
 154 implemented consistent with Simon's description. Of
 155 course, no decision process is this clear-cut in an ill-
 156 structured situation. Typically, the phases overlap and
 157 blend together, with frequent looping back to earlier
 158 stages as more is learned about the problem, as sol-
 159 utions fail, and so forth.

160 Over the last two decades or so, DSS research has
 161 evolved to include several additional concepts and
 162 views. Beginning in about 1985, group decision sup-

port systems (GDSS), or just group support systems 163
 (GSS), evolved to provide brainstorming, idea evalua- 164
 tion, and communications facilities to support team 165
 problem solving. Executive information systems (EIS) 166
 have extended the scope of DSS from personal or small 167
 group use to the corporate level. Model management 168
 systems and knowledge-based decision support sys- 169
 tems have used techniques from artificial intelligence 170
 and expert systems to provide smarter support for the 171
 decision-maker [5,12]. The latter began evolving into 172
 the concept of organizational knowledge management 173
 [47] about a decade ago, and is now beginning to ma- 174
 ture. 175

In the 21st century, the Internet, the Web, and tele- 176
 communications technology can be expected to result 177
 in organizational environments that will be increasingly 178
 more global, complex, and connected. Supply chains 179
 will be integrated from raw materials to end consumers, 180
 and may be expected to span the planet. Organizations 181
 will interact with diverse cultural, political, social, 182
 economic and ecological environments. Mitroff and 183
 Linstone [43] argue that radically different thinking is 184
 required by managers of organizations facing such 185
 environments; thinking that must include consideration 186
 of much broader cultural, organizational, personal, 187
 ethical and aesthetic factors than has often been the 188
 case in the past. Courtney [11], following Mitroff and 189

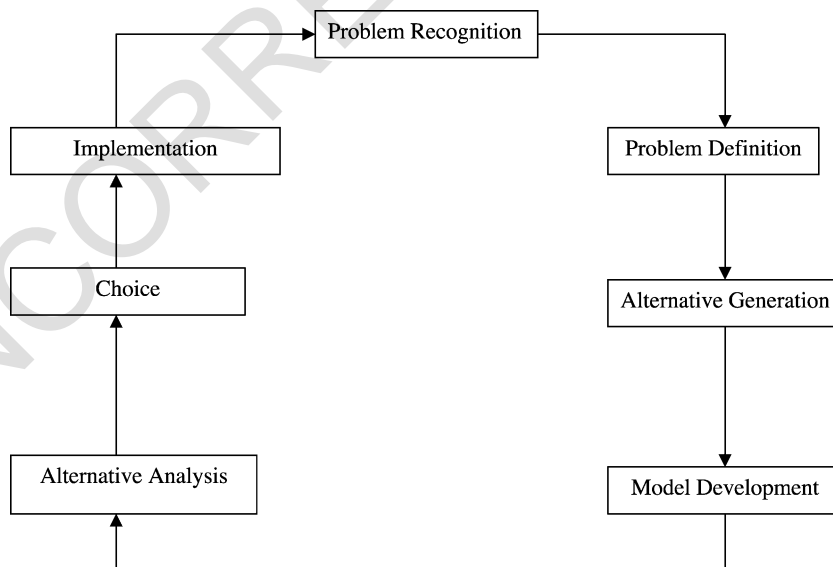


Fig. 1. The DSS decision-making process.

190 Linstone, suggests that DSS researchers should em-
 191 brace a much more comprehensive view of organiza-
 192 tional decision making (see Fig. 2) and develop deci-
 193 sion support systems capable of handling much
 194 “softer” information and much broader concerns than
 195 the mathematical models and knowledge-based sys-
 196 tems have been capable of handling in the case in the
 197 past. This is an enormous challenge, but is imperative
 198 that we face if DSS is to remain a vital force in the
 199 future.

200 The primary difference between Fig. 2 and typical
 201 decision models in a DSS context is the development
 202 of multiple and varied perspectives during the prob-
 203 lem formulation phase. Mitroff and Linstone [43]
 204 suggest that perspectives be developed from organiza-
 205 tional (O), personal (P) and technical (T) positions. In
 206 addition, ethical and aesthetic factors are considered
 207 as well. The mental models of stakeholders with
 208 various perspectives lie at the heart of the decision
 209 process, from defining what *is* a problem, to analysis
 210 of the results of trying to solve the problem.

211 The technical perspective has dominated DSS prob-
 212 lem formulation in the past, and involves the develop-
 213 ment of databases and models. The organizational and
 214 personal perspectives are developed by discussing the
 215 problem with all affected stakeholders, at least as re-
 216 sources permit, so as to ensure that all relevant varia-
 217 bles are either included in models, or taken into account
 218 during the analysis, if they cannot be quantified. As
 219 many of these factors may be more humanistic and
 220 nonquantifiable, especially ethical and aesthetic con-
 221 cerns. The need for broader forms of analysis, such as

group sessions, may become even more appropriate in
 the future.

The remainder of the paper discusses recent and
 expected DSS developments in more detail. First, re-
 cent activity in data warehousing, online analytical
 processing (OLAP), data mining and Web-based DSS
 is considered, followed by treatment of collaborative
 support systems and optimization-based decision sup-
 port.

3. Data warehouses, OLAP, data mining, and web-based DSS

Beginning in the early 1990s, four powerful tools
 emerged for building DSS. The first new tool for
 decision support was the data warehouse. The two
 new tools that emerged following the introduction of
 data warehouses were on-line analytical processing
 (OLAP) and data mining. The fourth new tool set is
 the technology associated with the World Wide Web.
 The Web has drawn enormous interest in the past few
 years and it can have an even greater impact in the years
 ahead. All of these tools remain “hot” topics in
 corporate and academic computing publications. This
 section attempts to briefly examine the past, present
 and future of these four decision support technologies.

The roots of building a data warehouse lie in
 improved database technologies. Initially, Codd [8]
 proposed the relational data model for databases in
 1970. This conceptual data base model has had a large
 impact on both business transaction processing sys-

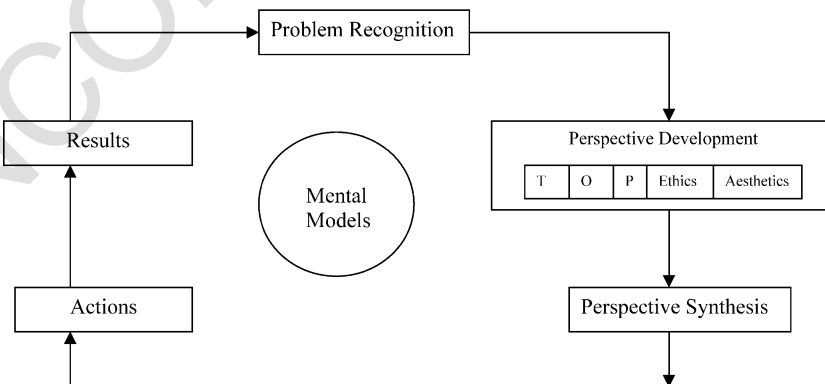


Fig. 2. A new decision paradigm for DSS. Source: Courtney [11].

tems and decision support systems. More recently, Codd's specification [9] of on-line analytical processing (OLAP) standards has had an equally large impact on the creation of sophisticated data-driven DSS [50]. In the early 1990s, only a few custom-built data warehouses existed. The work of Inmon [29], Devlin, and Kimball [33] promoted a data warehouse as a solution for integrating data from diverse operational databases to support management decision making. A data warehouse is a subject-oriented, integrated, time-variant, nonvolatile collection of data [29]. Many companies have built data warehouses, but there has been an ongoing debate about using relational or multidimensional database technologies for on-line analytical processing [55,59]. Both database technologies are currently used and relational structures like the star schema are preferred for very large data warehouses.

Building a large data warehouse often leads to an increased interest in analyzing and using the accumulated historical DSS data. One solution is to analyze the historical data in a data warehouse using on-line analytical processing tools. "On-line analytical processing (OLAP) is a category of software technology that enables analysts, managers, and executives to gain insight into data through fast, consistent, interactive access to a wide variety of possible views of information that has been transformed from raw data to reflect the real dimensionality of the enterprise as understood by the user." [45]

OLAP tools have become more powerful in recent years, but a set of artificial intelligence and statistical tools collectively called data mining tools [16] has been proposed for more sophisticated data analysis. Data mining is also often called database exploration, or information and knowledge discovery. Data mining tools find patterns in data and infer rules from them [50]. The rapidly expanding volume of real-time data, resulting from the explosion in activity from the Web and electronic commerce, has also contributed to the demand for and provision of data mining tools. A new category of firms, termed "infomediaries," will even conduct real-time data mining analysis of so-called "clickstream data" on behalf of their customers, who are typically highly interactive websites that generate a lot of data where managers wish to grasp the buying patterns of their visitors.

The Web environment is emerging as a very important DSS development and delivery platform. The

primary Web tools are Web servers using Hypertext Transfer Protocol (HTTP) containing Web pages created with Hypertext Mark-up Language (HTML) and JavaScript accessed by client machines running client software known as browsers. This environment traces its roots to original research by Tim Berners-Lee, who in 1990 developed a point-and-click hypertext editor, which ran on the "NeXT" machine. Berners-Lee released this editor and the first Web server to a narrow technical audience in the summer of 1991 (cf., <http://www.w3.org/People/Berners-Lee/ShortHistory.html>). His innovation led to the exciting developments in e-business and e-commerce by the end of the 1990s.

At the beginning of the 21st century, the Web is the center of activity in developing DSS. When vendors propose a Web-based DSS, they are referring to a computerized system that delivers decision support information or decision support tools to a manager or business analyst using a Web browser such as Netscape Navigator or Internet Explorer [50]. The computer server that is hosting the DSS application is linked to the user's computer by a network with the TCP/IP protocol. Most Web data warehouses support a four-tier architecture in which a Web browser sends HTML requests using HTTP to a Web server. The Web server processes these requests using a Common Gateway Interface (CGI) script. The script handles Structured Query Language (SQL) generation, post-SQL processing, and HTML formatting. This application server then sends requests to a database server, which generates the query result set and sends it back for viewing using a Web browser. Many technology improvements are occurring that are speeding up query processing and improving the display of results and the interactive analysis of data sets.

Web-based DSS have reduced technological barriers and made it easier and less costly to make decision-relevant information and model-driven DSS [50] available to managers and staff users in geographically distributed locations. Because of the Internet infrastructure, enterprise-wide DSS can now be implemented in geographically dispersed companies and to geographically dispersed stakeholders including suppliers and customers at a relatively low cost. Using Web-based DSS, organizations can provide DSS capability to managers over a proprietary intranet, to customers and suppliers over an extranet, or to any stakeholder over the global Internet. The Web has

347 increased access to DSS and it should increase the use
348 of a well-designed DSS in a company. Using a Web
349 infrastructure for building DSS improves the rapid
350 dissemination of “best practices” analysis and deci-
351 sion-making frameworks and it should promote more
352 consistent decision making on repetitive tasks.

353 Web-based DSS vendors are rapidly innovating and
354 mergers between vendors are common. Any analysis of
355 the features of data warehouse, OLAP, data mining or
356 other Web-based DSS products is obsolete before it is
357 completed. A Web site like The Data Warehousing
358 Information Center (<http://www.dwinformcenter.org>) has
359 an extensive list of tools and tool vendors. The DSSRe-
360 sources.COM Vendors page at URL <http://www.dssresources.com/vendorlist/> lists more than 75 companies
361 that market DSS products. Many of these vendors have
362 Web-based DSS products. A number of vendors have
363 examples of products at their Web sites.

365 Building DSS with these new tools remains a com-
366 plex analytical task. Some consultants use industry
367 specific templates for data warehouses, others use
368 structured design methodologies. Vendors promote
369 Web-enable business intelligence software and Web
370 portal software as a means to speed the development of
371 Web-based DSS. In some situations, an existing data
372 warehouse can be Web-enabled or made available
373 using a Web browser, but the data storage systems
374 may have problems serving an increased number of on-
375 line users. Web-based DSS with data warehouses and
376 OLAP are available 7 days a week and 24 hours a day,
377 so the needs of users have changed. Web database
378 architectures must handle a large number of concurrent
379 requests, while maintaining consistent query response
380 times as the number of users and volume of data
381 changes and will likely increase over time.

382 In most data mining applications, a data file of query
383 results is created from a data warehouse and then
384 analyzed by a specialist using artificial intelligence or
385 statistical tools. This new data file could be made
386 available through an Intranet to a broad group of
387 business analysts by client-server technologies. In the
388 21st century, both e-commerce and customer relation-
389 ship management (CRM) will increase the demand for
390 more analysis of customer transaction data. Many
391 software vendors and publications, such as Datamation
392 (<http://www.datamation.com/dataw/>), are suggesting
393 that all knowledge workers will become data miners
394 in the future. This potential use of the technologies

395 would likely lead to poorly conceived end-user analy-
396 ses and dubious results. In many academic disciplines,
397 data mining is viewed disparagingly as “data dredg-
398 ing.” Knowledgeable, well-trained business users need
399 to work with the data mining classification and cluster-
400 ing tools. Making tools like neural networks, decision
401 trees, rule induction, and data visualization widely
402 available to naïve users using Web technologies will
403 be a mistake.

404 So where does the Web lead the technologies of data
405 warehousing, OLAP, data mining and model-driven
406 DSS? The universal TCP/IP protocol or Web platform
407 leads to widespread use and adoption of decision
408 support systems in organizations. Managers who have
409 not used DSS will find the new tools powerful and
410 convenient. New managers, sales staff and others who
411 were not exposed to client-server tools or other DSS
412 tools of the 1980s and 1990s will expect DSS to be easy
413 to use and available from their office, home, and client/
414 customer locations.

4. Collaborative support systems¹

415
416 One of the more significant trends over the past 20
417 years has been the evolution from individual stand-
418 alone computers to the highly interconnected telecom-
419 munications network environment of today. Initially,
420 computers within firms were connected via local area
421 networks (LANs), allowing teams and workgroups to
422 share decision-making information more easily. Then,
423 firms began to connect their networks in wide area
424 networks to facilitate sharing of information across
425 organizational boundaries. Finally, the Internet and
426 Web created an environment with almost ubiquitous
427 access to a world of information. At the same time,
428 many organizational decisions migrated from individ-
429 ual decisions to ones made by small teams to complex
430 decisions made by large diverse groups of individuals
431 within a firm or even from multiple firms. In this en-
432 vironment, several key technological developments
433 have occurred in the area of decision support. Various
434 tools to support collaboration and group processes have
435 been developed, implemented, evaluated, and refined.

¹ Note: Certain elements from this section are adapted from Ref. [58].

437 4.1. Group processes supporting decision making

438 Individuals often make decisions in small groups or
 439 in large organizational networks. Alavi and Keen [1]
 440 define a business team as a “small, self-regulating, self-
 441 contained task-oriented work group” that “typically
 442 focus on organizationally assigned tasks.” *Collabora-
 443 tion* occurs within the context of cooperative work and
 444 is defined as “multiple individuals working together in
 445 a planned way in the same production process or in
 446 different but connected production processes” [60].
 447 Because individuals who cooperate or perform tasks
 448 together share only partially overlapping goals, indi-
 449 vidual group members’ activities must be *coordinated*
 450 to ensure that the disparate individuals come to share
 451 the same goals. Coordination involves actors working
 452 together harmoniously [37,38] to accomplish a collec-
 453 tive set of tasks [56]. A group decision results from
 454 interpersonal communication among group members
 455 [14].

456 4.2. Group support systems

458 Group support systems (GSS) or collaboration sup-
 459 port systems enhance the communication-related activi-
 460 ties of team members engaged in computer-supported
 461 cooperative work. The communication and coordina-
 462 tion activities of team members are facilitated by tech-
 463 nologies that can be characterized along the three
 464 continua of time, space, and level of group support
 465 [1,14,30]. Teams can communicate synchronously or
 466 asynchronously; they may be located together or
 467 remotely; and the technology can provide task support
 468 primarily for the individual team member or for the
 469 group’s activities. These technologies are utilized to
 470 overcome space and time constraints that burden face-
 471 to-face meetings, to increase the range and depth of
 472 information access, and to improve group task perform-
 473 ance effectiveness, especially by overcoming “process
 474 losses” [41,42]. In short, GSS facilitates more effective
 475 group interaction, leading to greater decision-making
 476 effectiveness in modern distributed organizations. [58]
 477 GSS and computer-mediated communication sys-
 478 tems (CMCS) provide support for either synchronous
 479 or asynchronous meetings. Synchronous meetings are
 480 spontaneous where ideas are exchanged with little
 481 structure. Participants communicate with each other
 482 in such a way that it is sometimes difficult to attribute

an idea to one participant or establish the reason behind 483
 a particular decision. It is estimated that managers 484
 spend 60% of their communication time in synchro- 485
 nous meetings [46], which include face-to-face meet- 486
 ings, telephone calls, desktop conferencing, certain 487
 group decision support systems (GDSS), and Web- 488
 based “chat rooms.” 489

On the other hand, asynchronous meetings are more 490
 structured than synchronous meetings. These meetings 491
 rely more on documents exchanged among partici- 492
 pants. Compared to synchronous meetings, asynchro- 493
 nous meeting participants have longer to compose their 494
 messages and, therefore, it is easy to attribute an idea 495
 to its originator and establish the reason behind a 496
 particular decision. However, asynchronous meetings 497
 require more time than synchronous meetings because 498
 information exchange takes longer. Asynchronous 499
 meetings are frequently used by groups where at least 500
 one participant is in a remote location [34]. Technol- 501
 ogies that facilitate asynchronous meetings include e- 502
 mail, bulletin board systems, and Internet newsgroups. 503
 Computer conferencing, which is a “structured form 504
 of electronic mail in which messages are organized by 505
 topic and dialogues are often mediated” [3,27], can be 506
 asynchronous (such as bulletin board systems and 507
 Internet newsgroups) or synchronous (such as “chat 508
 rooms”). 509

510 4.3. Virtual teams and the impact of technology

As decision making moves from an individual acti- 512
 vity toward a group one, many organizations are 513
 forming “virtual teams” of geographically distributed 514
 knowledge workers to collaborate on a variety of 515
 workplace tasks. The effects of the reduced “commu- 516
 nication modalities” on virtual team members and the 517
 circumstances in which these effects occur has been 518
 the focus of much of the CMCS research [28,42]. Al- 519
 though not definitive in terms of specific effects, the 520
 research in this area suggests that virtual teams com- 521
 municate differently than face-to-face groups [6,25, 522
 42,58]. While there is a plethora of research describ- 523
 ing various technologies for computer-mediated com- 524
 munications, there is a lack of studies examining 525
 “sustained, project-oriented teamwork of the sort that 526
 is important in most real-world organizations” [20]. 527
 An analysis of CMCS communication characteristics 528
 is warranted. 529

530 Collaboration support systems play a central role in
 531 facilitating communication among members of virtual
 532 teams. The technology imposes constraints on com-
 533 munication that are likely to affect a group's perform-
 534 ance. People rely on multiple modes of communication
 535 in face-to-face conversation, such as paraverbal (tone
 536 of voice, inflection, voice volume) and nonverbal (eye
 537 movement, facial expression, hand gestures, and other
 538 body language) cues. These cues help regulate the flow
 539 of conversation, facilitate turn taking, provide feed-
 540 back, and convey subtle meanings. As a result, face-to-
 541 face conversation is a remarkably orderly process. In
 542 normal face-to-face conversation, there are few inter-
 543 ruptions or long pauses and the distribution of partic-
 544 ipation is consistent, though skewed toward higher
 545 status members [36,40]. Collaboration support systems
 546 preclude these secondary communication modes, thus
 547 altering the orderliness and effectiveness of informa-
 548 tion exchange. Such communication modalities are
 549 constrained to a varying extent depending on the cha-
 550 racteristics of the technological system. For example,
 551 electronic mail prevents both paraverbal and nonver-
 552 bal cues, telephone conference calls allow the use of
 553 most paraverbal cues (but not nonverbal ones), while
 554 videoconferencing enables extensive use of both para-
 555 verbal and nonverbal cues. The lack of these cues
 556 reduces the richness of the information transmitted by
 557 virtual team members. Daft and Lengel [13] define
 558 media richness as "the ability of information to change
 559 understanding within a time interval." Rich media
 560 allow multiple information cues (the words spoken,
 561 tone of voice, body language, etc.) and feedback. It
 562 takes more time and effort by group members to
 563 achieve the same level of mutual understanding in a
 564 lean medium, such as CMCS, than in a rich one such as
 565 face-to-face communication. This communication con-
 566 straint affects the group's ability to reach a consensus
 567 decision.

568 Because virtual teams communicate less efficiently
 569 than face-to-face groups [25,26,42], they tend to be
 570 more task-oriented and exchange less social–emo-
 571 tional information, slowing the development of rela-
 572 tional links [6]. Development of relational links is
 573 important because researchers have associated strong
 574 relational links with many positive outcomes inclu-
 575 ding enhanced creativity and motivation, increased
 576 morale, fewer process losses, and better decisions
 577 [57,58].

4.4. Creating effective virtual teams

579

580 Face-to-face teams generally report greater satisfac-
 581 tion with the group interaction process than virtual
 582 teams [57,58]. Therefore, since virtual teams are
 583 becoming a necessary tool, organizations must strive
 584 to bolster the satisfaction level of CMCS. If this were
 585 accomplished, there would be no significant drawback
 586 to the use of virtual teams, which can be made more
 587 acceptable and satisfying in several ways. Zack [61]
 588 showed that the highly interactive nature of face-to-
 589 face meetings makes this mode "appropriate for build-
 590 ing a shared interpretive context among group mem-
 591 bers, while [CMCS], being less interactive, is more
 592 appropriate for communicating within an established
 593 context." Ongoing groups have an established culture
 594 and set of routines, and may have a greater commitment
 595 to achieving effective communications. Further, Zack
 596 suggested that while "social presence" (a sense of be-
 597 longing) is diminished in virtual teams, it is the lack of
 598 interactivity that primarily constrains computer medi-
 599 ated communication.

600 Users of CMCS must exercise leadership and influ-
 601 ence with little means of social control, and some
 602 members may become "lost in cyberspace" and may
 603 "drop out" of virtual teams in the absence of familiar
 604 communications patterns. Care must be exercised to
 605 develop and foster familiarity and proficiency with
 606 these new tools and techniques of social interaction.
 607 The most important goal of CMCS is to foster inter-
 608 action, inclusion and participation [39], which are all
 609 related to the feeling of "being there" or social pres-
 610 ence [61]. Social presence defines the extent to which a
 611 communications medium allows participants to expe-
 612 rience each other as being psychologically close or
 613 present [19]. Face-to-face communication, for exam-
 614 ple, is characterized by social cues such as nonverbal
 615 and paraverbal communications channels and contin-
 616 uous feedback [52]. The success of group support
 617 systems lies in part on their ability to provide the par-
 618 ticipants with socioemotional content sharing. Clearly,
 619 videoconferencing offers a greater opportunity for
 620 sharing these social cues than text-based communica-
 621 tions modes, yet the latter do not entirely lack such cues
 622 [51,57]. Designers of GSS should explicitly work to
 623 incorporate innovative methods and channels for shar-
 624 ing various cues between participants, such as "emo-
 625 tions" (also known as "smileys") to increase the

626 media richness of their communications. Whereas
 627 many first-time users of CMCS such as e-mail might
 628 write formal messages that read like business letters,
 629 the messages of high-volume users usually evolve into
 630 a far more familiar tone with personal comments and
 631 common terms and abbreviations that can create a
 632 greater sense of actually speaking with someone.

633 Kraut et al. [35] suggest that whereas formal com-
 634 munication is characterized by preset agendas between
 635 arranged participants scheduled in advance with “im-
 636 poverished content,” informal communication often
 637 occurs spontaneously with no arranged agenda be-
 638 tween random participants with richer content. Further,
 639 they show that informal encounters create a common
 640 context and perspective that support planning and
 641 coordination of group work. Without informal ex-
 642 changes, “collaboration is less likely to start and less
 643 productive if it does occur” [35]. Participants in purely
 644 computer-mediated systems who have never met and
 645 exchanged informal conversation have exhibited a
 646 strong desire to do so when given the opportunity—
 647 GSS developers should facilitate informal face-to-face
 648 contact wherever possible.

649 In the future, organizations introducing these deci-
 650 sion support technologies into the workplace must
 651 leverage the beneficial differences inherent in com-
 652 puter-mediated communications and mitigate the neg-
 653 ative differences. Managers must become familiar with
 654 the strengths and limitations of the relevant technolo-
 655 gies. The use of collaborative support systems will in-
 656 crease as the Web enables more strategic alliances and
 657 as intranets become a widespread platform for group
 658 decision making.

659 5. Optimization-based decision support models

660 This section describes the state of the art of opti-
 661 mization-oriented decision support, and speculates on
 662 the future of such systems. Model-based decision
 663 support can be divided into three stages: formulation,
 664 solution, and analysis. *Formulation* refers to the gen-
 665 eration of a model in the form acceptable to a model
 666 solver. The *solution* stage refers to the algorithmic
 667 solution of the model. The *analysis* stage refers to the
 668 ‘what-if’ analyses and interpretation of a model sol-
 669 ution or a set of solutions. The development of DSS
 670 tools to support these three stages has occurred at

different rates. Research in optimization traditionally
 focused on generating a better solution algorithm; as
 the technologies have evolved, more progress has been
 made in the formulation and analysis functions of DSS
 support.

5.1. Formulation

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Converting a decision-maker’s specification of a
 decision problem into an algebraic form and then into
 a form understandable by an algorithm is a key step in
 the use of a model. We have come a long way from the
 days of requiring an optimization problem to be input
 in the commonly used Mathematical Programming
 System (MPS) format. Several algebraic modeling
 language processor systems (AMLPS) have been de-
 veloped that make it convenient to input the modeler’s
 form of an optimization problem directly into a solver.
 These AMLPS also can read and write data files from/
 to many diverse databases, enabling a truly integrated
 model generation. Some of these AMLPS support
 ODBC calls and thus now can be used for development
 of a model that depends upon many data sources
 located across an enterprise. Indeed, the growth in
 these systems is now leading to the development of a
 Modeling Environment (ME) where the solver takes a
 support role. The ME serves as the model translator and
 manager of all input/output and interaction with the
 user. These systems are extensible through a link to any
 other solver.

The next generation of formulation support is dis-
 played in further integration of the model specification
 in host computing platforms. Modeling Environments
 are becoming available as APIs so that these can be
 called directly into an end-user application. The for-
 mulation support is also extended through the growth
 of enterprise resource planning (ERP) movement.
 Optimization-based DSS will play a key role in the
 next wave of ERP software, and the modeling lan-
 guages will make it happen.

5.2. Solution

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Historically, most of the research effort in operations
 research (OR) has been concentrated on development
 of new algorithms to solve problems faster. The good
 news is that decision support software developers
 appear to incorporate advances in the solution algo-

717 rithms quite quickly to let the user benefit from these
718 enhancements. Some major trends are highlighted
719 below.

720 The traditional linear programming software con-
721 tinues to be refined in both simplex method and interior
722 point algorithms. The emphasis is on taking advantage
723 of problem characteristics to reduce the problem size or
724 to speed up a specific algorithmic step. The result is the
725 ability to solve really large problems. It has also en-
726 abled the modelers to consider uncertainty in the de-
727 cision situation through stochastic programming with
728 recourse type approaches.

729 Perhaps the biggest gains in the solution algorithms
730 are evident in the mixed-integer programming (MIP)
731 arena. With the incorporation of various tricks, solu-
732 tions of much larger MIP problems are now possible. A
733 major development is the solution of integer program-
734 ming problems is the use of constraint logic program-
735 ming [17,18]. This approach employs the tree search
736 philosophy of branch and bound, but does not require
737 solution of LP problems.

738 The next major trend in the solution software is the
739 growth of metaheuristics to solve combinatorial prob-
740 lems [21,22]. The techniques employed include tabu
741 search, genetic algorithms, simulated annealing, neural
742 networks, and several others. For example, Evolver is a
743 commercially available tool (from Palisades Software)
744 that solves MIP problems using genetic algorithms.
745 The combination of techniques from artificial intelli-
746 gence and operation research to attack much larger
747 problems is going to benefit the DSS movement in the
748 next few decades.

749 Traditionally sold optimization software is becom-
750 ing a foundation in the DSS platform. A casual look at a
751 recent issue of *ORMS Today* would show advertise-
752 ments from companies such as Maximal Software
753 offering their solver in Application Programming Inter-
754 face (API) form to XA offering their product for full
755 integration in ABAP/4, SAP's programming language.

756 5.3. Analysis

758 Only recently have vendors of optimization soft-
759 ware begun to focus on the final stage of the modeling
760 process—analysis. This stage includes delivery of
761 model solution in a usable form to enhance the ability
762 to analyze and understand the problem and the solution.
763 Report generating functionality is now a common fea-

764 ture used to present the results to the user in a usable
765 form that can be integrated into databases. Solutions
766 can also be stored in popular spreadsheet formats for
767 simple graphical analyses or report generation. Some
768 modeling environments offer their own graphical dis-
769 play tools to display results in easy to use format. It is
770 likely that the growth of new visualization tools will
771 benefit the process of solution delivery in OR models as
772 well. It would be possible to incorporate multimedia in
773 highlighting solutions or especially exceptions to the
774 norm or signal infeasibilities.

775 The analysis stage has also benefited from incorpo-
776 ration of deductive techniques such as IIS [7] to diag-
777 nose the cause of infeasibilities or ANALYZE [24] to
778 perform post solution analysis beyond the classic
779 sensitivity analysis. A new trend is the ability to store
780 and analyze multiple solution scenarios. The Scenario
781 Manager tool within Microsoft Excel popularized the
782 concept of saving multiple solutions and understands
783 any underlying patterns. Some researchers [53] have
784 proposed the use of inductive analysis techniques to
785 further generate insight into the problem by studying
786 multiple solutions. The concept of generating multiple
787 ‘what-if’ scenarios and solutions is now available in
788 commercial software such as Risk Optimizer from
789 Palisade Software.

790 We have seen many developments in analytical
791 models, optimization and model-based DSS, but the
792 possibilities for greater exploitation of models in deci-
793 sion making are enormous. In the next section, we
794 examine some broader issues in actively supported ma-
795 nagement decision making.

796 6. Active decision support for the next millennium

797 The need for active decision support was asserted
798 by Keen [31] when he outlined “the next decade of
799 DSS” in 1987. His first point is that the DSS technol-
800 ogy itself is not important—it is the *support* we intend
801 to provide which is the key element. Keen gave DSS
802 research the following broad agenda: (i) it should look
803 for areas where the proven skills of DSS builders can
804 be applied in new, emergent or overlooked areas; (ii) it
805 should make an explicit effort to apply analytic models
806 and methods; it should embody a far more prescriptive
807 view of how decisions can be made more effectively;
808 (iii) it should exploit the emerging software tools and

809 experience base of AI to build semi-expert systems,
810 and (iv) it should re-emphasise the special value of
811 DSS practitioners as being their combination of exper-
812 tise in understanding decision making and knowing
813 how to take advantage of developments in computer-
814 related fields.

815 We will use Keen's agenda for "the next decade of
816 DSS", but we will update it from 1987 to 1997, and
817 look ahead to the year 2007. Managers and knowledge
818 workers in the late 1980s and 1990s are different from
819 earlier DSS users, and will be quite different from those
820 of 2007. Technological proficiency levels of all users
821 continue to increase. The compromises we made with
822 system designs in order to facilitate the use of DSS by
823 inexperienced users in the late 1980s will not be
824 necessary for the users of the 2007. On the other hand,
825 this new generation of technologically advanced users
826 will also expect more functionality in DSS technology.
827 The DSS technology of the future will be enhanced by
828 mobile tools, mobile e-services, and wireless protocols
829 such as Wireless Applications Protocol (WAP), Wire-
830 less Markup Language (WML), and iMode, thereby
831 leading to ubiquitous access to information and deci-
832 sion support tools. Greater collaboration functions will
833 be enabled, facilitating more interactive decision pro-
834 cesses.

835 In the last few years, we have seen a steady inflow of
836 models and tools for multiple-criteria decision making
837 in DSS applications (Keen's second point), and it
838 appears that this will continue as developers incorpo-
839 rate more advanced mathematical programming soft-
840 ware integrated with (for instance) MS Excel. The use
841 of artificial intelligence (AI), as advocated in Keen's
842 third point, is being replaced with intelligent systems
843 and soft computing, which are emerging new techno-
844 logical platforms. In fact, rather than stand-alone AI
845 modules, intelligent logic is now usually inherent in the
846 processing of all decision support tools.

847 Because more senior executives are comfortable
848 with information technology (IT), the roadblocks of
849 the 1980s and 1990s for using IT in executive decision
850 making are being removed. In fact, IT is now viewed as
851 a strategic tool that is central to the pursuit of com-
852 petitive advantage. Therefore, various DSS technolo-
853 gies will be more accepted throughout the enterprise,
854 from operational support to executive boardrooms.
855 Further, modern corporations and their strategic busi-
856 ness units will continue to lose their hierarchical

organizational structures. Companies seek to create 857
business entities that are leaner, more flexible and more 858
responsive to a rapidly changing business environment. 859
With reductions in staff and middle management per- 860
sonnel, senior managers and executives get more di- 861
rectly involved with problem solving, decision making 862
and planning than they were in the 1980s. Agile and 863
flexible organizations also ask their managers and staff 864
to frequently change their focus. Therefore, decision 865
support tools will play a more central role in this rapidly 866
changing environment. 867

868 The first target for intelligent systems technology
869 should be the overwhelming flow of data, information
870 and knowledge produced for executives by an increas-
871 ing number of sources. Expert systems technology,
872 which was a focal area for venture capital in 1985–
873 1990, is now being replaced by intelligent systems,
874 which are built to fulfill two key functions: (i) the
875 screening, sifting and filtering of a growing overflow of
876 data, information and knowledge (described above),
877 and (ii) the support of an effective and productive use of
878 the Executive Information Systems (EIS), which quite
879 often is tailored to the needs and the personality of the
880 user. Intelligent systems, which can be implemented for
881 these purposes, range from self-organizing maps to
882 smart add-on modules to make the use of standard
883 software more effective and productive for the users.
884 Intelligent data mining will also play a significant role
885 in helping organizations transform huge volumes of
886 data into valuable corporate knowledge and intelli-
887 gence.

888 Software agents (also called intelligent agents) have
889 also been designed and implemented to address this
890 process of data screening and filtering. These Java-
891 based components can be designed and implemented to
892 search for data sources with user-defined search pro-
893 files, to identify and access relevant data, to copy the
894 data, and to organize and store it in a data warehouse.
895 Other agents of the same "family" can then be used to
896 retrieve the data, insert it in reports and to distribute it
897 over e-mail according to topic-specific distribution
898 profiles.

7. Conclusions 899

900 The developments in the last decade will guide us
901 in understanding the coming evolution of decision

902 support technologies. Changes will occur in technol-
903 ogies and in the implementation environment—users
904 are becoming more sophisticated and more demand-
905 ing, organizations are becoming more complex yet
906 more agile and flexible, and global regulatory and
907 competitive factors rapidly change, affecting the
908 design and use of these tools. The future will offer
909 surprises, to be sure, but certain trends can be ob-
910 served.

911 One such trend is the meteoric rise of the Web as a
912 common platform from which to extend the capabil-
913 ities of DSS to a very large number of users. The fact
914 that a standard Web browser can be used as the user
915 interface/dialog means that companies can introduce
916 new DSS technologies at their sites at relatively low
917 cost when compared to client-based DSS. A Web
918 browser user interface allows the implementation of
919 DSS technology with very little user training. The
920 potential exists for web-based DSS to increase pro-
921 ductivity and profitability, and speed the decision
922 making process without regard to geographic limita-
923 tions. Through increased decision making ability,
924 reduced costs, and reduced support needs, Web-based
925 DSS can significantly improve companies' use of
926 their existing infrastructures. More executives and
927 managers can have access to technology that increases
928 overall organizational efficiency and effectiveness.

929 The Web also dramatically increases the usability
930 factors for DSS. Standard interface design factors
931 mean that users can more quickly adopt new DSS
932 with less training and with more confidence. How-
933 ever, while standards are advantageous from that
934 perspective, we also recommend that *personalization*
935 of the DSS user interface is a future area that should
936 be addressed by developers and researchers. The
937 processing power of today's platforms enables the
938 design of highly configurable interfaces that identify
939 the usage patterns of individual users and modify
940 themselves (by reducing menu choices, for example)
941 in order to provide higher usability for each DSS
942 user.

943 Another trend is the increasing sophistication of
944 model-based DSS software. For example, model-
945 based DSS software is standardizing on Web tech-
946 nologies as the fundamental technology for interface
947 design. Most major DSS software developers now
948 have websites and offer downloading trial software
949 for further exploration. Even more exciting is the

trend toward using the Application Service Provider 950
(ASP) model for delivery of DSS functionality. DSS 951
software customers no longer need to purchase and 952
install the software on their own servers; they may 953
just rent it on a per-use basis from an ASP who hosts 954
the decision support application and provides secure 955
access over the Internet. This is especially useful for 956
solver software so that a modeler can employ the best 957
solver software appropriate for a specific situation 958
without having to buy every single program. Exam- 959
ples of this approach include IBM's OSL site ([http://](http://www.research.ibm.com/osl/bench.html) 960
www.research.ibm.com/osl/bench.html) and the 961
NEOS Server (<http://www.mcs.anl.gov/otc/Server/>). 962
Bhargava et al. [4] have been developing Decision 963
Net (<http://www.ini.cmu.edu/emarket/>) as a portal to 964
enable the modeler to rent a specific program on a per 965
use basis. 966

967 A major trend is how the Web is supporting more 967
interactivity and collaboration in DSS. Organizations 968
are building not only virtual team structures, but also 969
entire virtual organizations, based on this technol- 970
ogical platform. With the application of intranets and 971
enterprise resource planning (ERP) systems, entire 972
organizations routinely interact via technology with 973
little or no face-to-face interaction. Such virtual organ- 974
izations have seemingly overcome all barriers of time 975
and space, and have created entire firms with remote 976
business partners. A final trend in this domain is the 977
development of *ubiquitous computing* based on secure 978
wireless band width and new "thin client" devices 979
such as Web-enabled digital phones and digital assis- 980
tants. In this environment, virtual teammates can truly 981
collaborate anywhere and anytime. Without the need 982
to physically be at a computer tied to a wired network, 983
individuals are free to collaborate more naturally and 984
nearly all the time. This ensures even greater connec- 985
tivity to members of workgroups and virtual teams, 986
with greater access and more robust decision support. 987
Another benefit of this wireless interactivity is the 988
enhancement of the ability of knowledge workers to 989
collect multiple perspectives on decision problems as 990
suggested in Fig. 2. Using the multiple perspectives 991
approach to problem formulation should help lead us 992
towards Keen's goal of finding areas where tools can 993
be developed for turning qualitative insights and 994
uncertain and incomplete data into useful knowledge. 995
Ultimately, this new environment allows individuals 996
and organizations to make more informed, more col- 997

998 laborative decisions that will achieve the organiza-
999 tion's goals more effectively.

1000 Though information technology is advancing the
1001 form, style, and content of decision support, we believe
1002 the development of model-based DSS is still at an early
1003 stage, and finally poised to emerge as a powerful tool
1004 for managerial support. One of the challenges in em-
1005 ploying models for decision support has been the
1006 availability of data from across various data ware-
1007 houses within an organization. The client server model
1008 of the web allows more transparent access to this data,
1009 making it possible to run models based on actual data.
1010 In a recent paper, Cohen et al. [10] describe several
1011 implementations of optimization-based DSS that inte-
1012 grate data from several sources. Many optimization
1013 software providers and professional service organiza-
1014 tions are building specific interfaces to bring all the data
1015 together to make these applications possible. The
1016 extraordinary growth of i2 Technologies and many
1017 other companies that employ optimization models to
1018 enhance the supply chain is a good example. Growth of
1019 the Internet enables smaller organizations to also
1020 employ some of the same tools. This opportunity will
1021 grow substantially and result in the next generation of
1022 cheaper, faster, and better DSS tools for a much larger
1023 client base than we have seen before.

1024 By extending Keen's agenda for DSS research to the
1025 year 2007, we can reformulate it with the potential
1026 support of the new technologies. DSS researchers and
1027 developers should (i) identify areas where tools are
1028 needed to transform uncertain and incomplete data,
1029 along with qualitative insights, into useful knowledge;
1030 (ii) be more prescriptive about effective decision mak-
1031 ing by using intelligent systems and methods; (iii)
1032 exploit advancing software tools to improve the pro-
1033 ductivity of working and decision making time, and
1034 (iv) assist and guide DSS practitioners in improving
1035 their core knowledge of effective decision support.
1036 This process will be enhanced by continued develop-
1037 ments in Web-enabled tools, wireless protocols, and
1038 group support systems, which will expand the inter-
1039 activity and pervasiveness of decision support technol-
1040 ogies.

1041 **8. Uncited reference**

1042 [48]

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1043

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References

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[1] M. Alavi, P.G.W. Keen, Business teams in an information age, *The Information Society* 6 (4) (1989) 179–195. 1049
1050
[2] R.N. Anthony, *Planning and Control Systems: A Framework for Analysis*, Harvard University Graduate School of Business Administration, 1965. 1051
1052
[3] R.M. Baecker, *Readings in Groupware and Computer-Supported Cooperative Work*, Morgan Kaufmann Publishers, San Mateo, CA, 1993. 1053
1054
[4] H.K. Bhargava, R. Krishnan, R. Müller, Decision support on demand: emerging electronic markets for decision technologies, *Decision Support Systems* 19 (1997) 193–214. 1055
1056
[5] R.H. Bonczek, C.W. Holsapple, A.B. Whinston, *Foundations of Decision Support Systems*, Academic Press, New York, 1981. 1057
1058
[6] L. Chidambaram, Relational development in computer-supported groups, *MIS Quarterly* 20 (2) (1996) 143–163. 1059
1060
[7] J.W. Chinneck, E.W. Dravnieks, Locating minimal infeasible constraint sets in linear programs, *ORSA Journal on Computing* 3 (2) (1991) 157–168. 1061
1062
[8] E.F. Codd, A relational model for large shared data banks, *Communications of the ACM* 13 (6) (1970) 370–387. 1063
1064
[9] E.F. Codd & Associates, "Providing OLAP (On-line Analytical Processing) to User-Analysts: An IT Mandate," a white paper, commissioned by Arbor Software (now Hyperion Solutions) 1993. 1065
1066
[10] M. Cohen, C.B. Kelly, A.L. Medaglia, Decision support with web-enabled software, *Interfaces* 31 (2) (2001), in press. 1067
1068
[11] J.F. Courtney, Decision making and knowledge management in inquiring organizations: toward a new decision-making paradigm for DSS, *Decision Support Systems*, (2001), in press. 1069
1070
[12] J.F. Courtney, D.B. Paradise, Studies in managerial problem formulation systems, *Decision Support Systems* 9 (1993) 413–423. 1071
1072
[13] R.L. Daft, R.H. Lengel, Organizational information requirements, media richness, and structural design, *Management Science* 32 (5) (1986) 554–571. 1073
1074
[14] G. DeSanctis, B. Gallupe, A foundation for the study of group decision support systems, *Management Science* 33 (12) (1987) 1589–1609. 1075
1076
[15] N. Earle, P. Keen, *From.Com to.Profit: Inventing Business Models that Deliver Value and Profit*, Jossey-Bass, 2000. 1077
1078
[16] H. Edelstein, Mining data warehouses, *Information Week*, January 8, 1996 (561) <http://www.techweb.com/se/directlink.cgi?IWK19960108S0035>. 1079
1080
[17] R. Fourer, Constraint logic programming for the design of mathematical programming systems, *INFORMS CSTS Conference*, Monterey. 1081
1082
1083
1084
1085
1086
1087
1088
1089
1090
1091
1092
1093
1094

- 1095 [18] R. Fourer, Software survey: linear programming, *OR/MS Today* 26 (4) (1999) 64–65. 11096
- 1097 [19] J. Fulk, B. Boyd, Emerging theories of communication in 11098 organizations, *Journal of Management* 17 (2) (1991) 407– 1099 446.
- 1100 [20] J. Galegher, R. Kraut, Computer-mediated communication for 1101 intellectual teamwork: an experiment in group writing, *Informa-* 1102 *tion Systems Research* 5 (2) (1994) 110–138.
- 1103 [21] F. Glove, M. Laguna, General purpose heuristics for integer 1104 programming—Part I, *Journal of Heuristics* 2 (1997) 343– 1105 358.
- 1106 [22] F. Glove, M. Laguna, General purpose heuristics for integer 1107 programming—Part II, *Journal of Heuristics* 3 (1997) 161– 1108 179.
- 1109 [23] G.A. Gorry, M.S. Scott Morton, A framework for management 1110 information systems, *Sloan Management Review* 13 (1) 1111 (1971) 50–70.
- 1112 [24] H.J. Greenberg, Intelligent analysis support for linear pro- 1113 grams, *Computer & Chemical Engineering* 16 (7) (1992) 1114 659–674.
- 1115 [25] R.T. Hightower, L. Sayeed, The impact of computer mediated 1116 communication systems on biased group discussion, *Compu-* 1117 *ters in Human Behavior* 11 (1) (1995) 33–44.
- 1118 [26] R.T. Hightower, L. Sayeed, Effects of communication mode 1119 and prediscussion information distribution characteristics on 1120 information exchange in groups, *Information Systems Re-* 1121 *search* 7 (4) (1996) 451–465.
- 1122 [27] S.R. Hiltz, M. Turoff, *The Network Nation: Human Commu-* 1123 *nication via Computer*, Addison-Wesley, 1978.
- 1124 [28] A.B. Hollingshead, J.E. McGrath, K.M. O'Connor, Group task 1125 performance and communication technology: a longitudinal 1126 study of computer-mediated versus face-to-face work groups, 1127 *Small Group Research* 24 (3) (1993) 307–333.
- 1128 [29] W.H. Inmon, *Building the Data Warehouse*, QED Information 1129 Sciences, Wellesley, MA, 1992.
- 1130 [30] R. Johansen, *Groupware: Computer Support for Business* 1131 *Teams*, The Free Press, New York, 1988.
- 1132 [31] P. Keen, Decision support systems: the next decade, *Decision* 1133 *Support Systems* 3 (3) (1987) 253–265.
- 1134 [32] P. Keen, M. Scott Morton, *Decision Support Systems: An Or-* 1135 *ganizational Perspective*, Addison-Wesley Publishing, 1978.
- 1136 [33] R. Kimball, *The Data Warehouse Toolkit*, Wiley, 1996.
- 1137 [34] S.T. Kinney, R.R. Panko, Project teams: profiles and member 1138 perceptions: implications for group support system research 1139 and products, *Proceedings of the Twenty-Ninth Hawaii Inter-* 1140 *national Conference on System Sciences*, Kihei, Maui, 1996, 1141 pp. 128–137.
- 1142 [35] R.E. Kraut, R.S. Fish, R.W. Root, B.L. Chalfonte, Information 1143 communication in organizations: form, function, and technol- 1144 ogy, in: R.M. Baecker (Ed.), *Readings in Groupware and* 1145 *Computer-Supported Cooperative Work*, Morgan Kaufmann 1146 Publishers, San Mateo, CA, 1993, pp. 287–314.
- 1147 [36] P.R. Laughlin, Social combination processes of cooperative, 1148 problem-solving groups as verbal intellectual tasks, in: M. 1149 Fishbein (Ed.), *Progress in Social Psychology*, vol. 1, Erl- 1150 baum, Hillsdale, NJ, 1980.
- 1151 [37] T.W. Malone, K. Crowston, What is coordination theory and 1152 how can it help design cooperative work systems? *Proceed-* 1153 *ings of the Conference on Computer-Supported Coopera-* 1154 *tive Work*, ACM, Los Angeles, 1990. 1155
- [38] T.W. Malone, K. Crowston, The interdisciplinary study of 1156 coordination, *ACM Computing Surveys* 26 (1) (1994) 87– 1157 119.
- [39] J.E. McGrath, Time, interaction, and performance (TIP): a 1158 theory of groups, *Small Group Research* 22 (2) (1991) 147– 1159 174. 1160
- [40] J.E. McGrath, Time matters in groups, in: J. Galegher R.E. 1161 Kraut, C. Egido (Eds.), *Intellectual Teamwork: Social and* 1162 *Technological Foundations of Cooperative Work*, Lawrence 1163 Erlbaum Associates, Hillsdale, NJ, 1990, pp. 23–62. 1164
- [41] J.E. McGrath, A.B. Hollingshead, Putting the “group” back in 1165 group support systems: some theoretical issues about dynamic 1166 processes in groups with technological enhancements, L.M. 1167 Jessup, J.S. Valacich (Ed.), *Group Support Systems: New Per-* 1168 *spectives*, Macmillan, New York, 1993. 1169
- [42] J.E. McGrath, A.B. Hollingshead, *Groups Interacting with* 1170 *Technology: Ideas, Evidence, Issues and an Agenda*, Sage 1171 Publications, London, 1994. 1172
- [43] I.I. Mitroff, H.A. Linstone, *The Unbounded Mind: Breaking* 1173 *the Chains of Traditional Business Thinking*, Oxford Univ. 1174 Press, New York, 1993. 1175
- [44] R.L. Nolan, D.C. Croson, *Creative Destruction*, Harvard Busi- 1176 ness School Press, Boston, MA, 1995. 1177
- [45] OLAP Council, Definitions, [http://www.dssresources.com/](http://www.dssresources.com/glossary/olaptrms.html) 1178 [olaptrms.html](http://www.dssresources.com/glossary/olaptrms.html), 1997. 1179
- [46] R.R. Panko, Patterns of managerial communication, *Journal of* 1180 *Organizational Computing* 2 (1) (1992) 95–122. 1181
- [47] D.B. Paradić, J.F. Courtney, Organizational knowledge man- 1182 agement, *Information Resources Management Journal* 2 (3) 1183 (1989) 1–13. 1184
- [48] J.C. Partyka, R.W. Hall, On the road to service, *ORMS Today* 1185 27 (4) (2000) 26–30. 1186
- [49] J.M. Pearson, J.P. Shim, An empirical investigation into DSS 1187 structures and environments, *Decision Support Systems* 13 1188 (1995) 141–158. 1189
- [50] D.J. Power, *Decision Support Systems Glossary*. DSS Re- 1190 sources, World Wide Web, [http://www.DSSResources.COM/](http://www.DSSResources.COM/glossary/) 1191 [glossary/](http://www.DSSResources.COM/glossary/), 1999. 1192
- [51] R.E. Rice, G. Love, Electronic emotion: socioemotional con- 1193 tent in a computer-mediated communication network, *Com-* 1194 *munication Research* 14 (1) (1987) 85–108. 1195
- [52] E.M. Rogers, *Communications Technology: The New Media* 1196 *in Society*, The Free Press, New York, 1986. 1197
- [53] R. Sharda, D. Steiger, Inductive model analysis systems: en- 1198 hancing model analysis in decision support systems, *Informa-* 1199 *tion Systems Research* 7 (3) (1996) 328–341. 1200
- [54] H.A. Simon, *The New Science of Management Decision*, Har- 1201 per Brothers, New York, 1960. 1202
- [55] E. Thomsen, *OLAP Solutions: Building Multidimensional In-* 1203 *formation Systems*, Wiley, New York, 1997. 1204
- [56] A.H. Van de Ven, A.L. Delbecq, R. Koenig, Determinants of 1205 coordination modes within organizations, *American Sociolog-* 1206 *ical Review* 41 (1976) 322–338. 1207
- [57] J.B. Walther, J.K. Burgoon, Relational communication in com- 1208

puter-mediated interaction, *Human Communication Research* 19 (1) (1992) 50–88.
 [58] M.E. Warkentin, L. Sayeed, R. Hightower, Virtual teams versus face-to-face teams: an exploratory study of a web-based conference system, *Decision Sciences* 28 (4) (1997) 975–996.
 [59] H. Watson, P. Gray, *Decision Support in the Data Warehouse*, Prentice-Hall, Englewood-Cliffs, NJ, 1997.
 [60] P. Wilson, Introducing CSCW—what it is and why we need it, in: S.A.R. Scrivener (Ed.), *Computer-Supported Cooperative Work*, Ashgate Publishing, Brookfield, VT, 1994.
 [61] M.H. Zack, Interactivity and communication mode choice in ongoing management groups, *Information Systems Research* 4 (3) (1993) 207–239.

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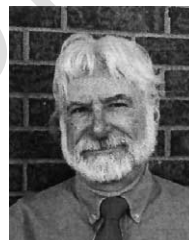
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