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An integrative evaluation framework for intelligent decision support systems

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Abstract

Evaluation of the overall effectiveness of decision support systems (DSS) has been a research topic since the early 1980s. As artificial intelligence methods have been incorporated into systems to create intelligent decision support systems (IDSS), researchers have attempted to quantify the value of the additional capabilities. Despite the useful and relevant insights generated by previous research, existing evaluation methodologies offer only a fragmented and incomplete view of IDSS value and the contribution of its technical infrastructure. This paper proposes an integrative, multiple criteria IDSS evaluation framework through a model that links the decision value of an IDSS to both the outcome from, and process of, decision making and down to specific components of the IDSS. The proposed methodology provides the designer and developer specific guidance on the intelligent tools most useful for a specific user with a particular decision problem. The proposed framework is illustrated by evaluating an actual IDSS that coordinates management of urban infrastructures.
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1. Introduction

Information systems and technology are an integral part of organizational decision making and management processes. As the technology advances, the deployment of information systems and technology in business and government increases rapidly. Even though the anecdotal evidence suggests that information systems and technology provides significant advantages in effectively and efficiently managing organizations, the contributions of information systems and technology have been questioned in several circles (see, for example Carr, 2003). Therefore, the issue of information systems pay-off, value, and benefit has been a topic of research (see for example, Brynjolfsson and Hitt, 1998; Devraj and Kohli, 2002; Kohli and Devaraj, 2003). The value of information is defined as "the difference between a decision maker's payoff in the absence of information relative to what can be obtained in its presence" (Banker and Kauffman, 2004). While so easy to define, it is extremely hard to measure because of the intricacies, efforts, and investments involved in creating the information systems and using the information technologies that produce information. Further, the value of information systems and technology is also influenced by their actual use in decision making (Devraj and Kohli, 2003). Research studies evaluating information systems and technology range from the pay-offs from investments (see, for example, Devraj and Kohli, 2002, 2003; Kohli and Devaraj, 2003) in information technology to the bottom line advantage of specific information technologies like Y2K (Anderson et al., 2006).

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The value of information to the decision maker is often measured indirectly by evaluating information systems against some surrogate criteria. For example, the value of a decision support system (DSS) such as that described by Sprague (1980) has been evaluated from the perspective of developing a DSS (Adelman, 1992; Akoka, 1981; Hitt and Brynjolfsson, 1996), improvements in the understanding and use of Simon's phases (1960) in the decision making process, and improvements in the outcomes from the use of the DSS (Forgionne, 1999, 2000). By themselves, none of these approaches provide a good measure of the decision value of DSS (Forgionne, 1999). They each provide an evaluation of a different worldview such as organizational, user, or technical. A worldview was defined by Checkland (2000) as the particular image or model of a part of the world that is being considered (e.g. context, problem task, and solution system) by an entity and that is usually biased by the entity's mindset of concepts, beliefs and values and their interrelationships (e.g. knowledge), and that becomes meaningful and relevant.

Combinations of evaluation criteria have been considered by Keen (1981), Chandler (1982), Kurikose (1985), Sharda et al. (1988), Santhanam and Guimaraes (1995), Forgionne and Kohli (2001), Manyard et al. (2001), Phillips-Wren et al. (2004), Sun and Kantor (2006) and Wang and Forgionne (2006). All of these authors have offered more complete frameworks and models, but all lack a holistic worldview that considers jointly the organizational, user, designer and builder criteria of interest. Such criteria are particularly needed for intelligent decision support systems (IDSS) since they may proactively impact the process of decision making as well as the outcome, by providing, for example, real-time response, distributed architectures, autonomous behaviour to support the decision maker, and Net-centric environments.

The extended models and frameworks have generally focused on organizational outcomes and decision-maker upper-level criteria with little examination of technical attributes. While organizational and decision-maker impacts are important, these benefits only can be achieved when the system adequately supports decisional services and tasks with suitably deployed architectural capabilities. This long-term decisional process-outcomes hypothesis or research premise, based in Artificial Intelligence frameworks posed for the design of intelligent systems in general (Newell, 1981), has been adapted as the IDSS hypothesis:

> "*Decision-making phases and steps can be improved by the support of decisional services and tasks, which are provided by architectural capabilities that can/could in the future be computationally implemented by symbol/program-based mechanisms*" (Mora et al., 2005).

This paper illustrates and implements the IDSS hypothesis by integrating a multiple criteria framework for DSS evaluation for the organizational outcomes and decision-maker processes (Forgionne, 1999, 2000; Phillips-Wren et al., 2006a,b) with the service-task, architectural and computational mechanisms deployed by the IDSS from an Artificial Intelligence perspective (Mora et al., 2005). The applicability of this integrated and enhanced model to evaluate an IDSS is demonstrated through an existing IDSS developed for the management of urban infrastructures (Quintero et al., 2005).

The rest of this paper is organized as follows. Section 2 briefly describes IDSS. The proposed comprehensive and integrative framework for IDSS design and evaluation is described in Section 3. Then, in Section 4, a multiple criteria evaluation model for an IDSS is developed and illustrated through the evaluation of an existing IDSS. This section also reports the results of the IDSS evaluation. Finally, Section 5 concludes the paper with brief comments on future directions for research.

2. Intelligent decision support systems (IDSS)

IDSS add artificial intelligence (AI) functions to traditional DSS with the aim of guiding users through some of the decision making phases and tasks or supplying new capabilities. This notion has been applied in various ways. For example, Linger and Burstein (1997) provided two layers in their framework for IDSS, a pragmatic layer associated with the actual performance of the task, and the conceptual layer associated with the processes and structure of the task. Using Linger and Burstein's (1997), and other, concepts, we can develop the IDSS architecture shown in Fig. 1 (Forgionne et al., 2005).

As Fig. 1 illustrates, an IDSS has a data base, knowledge base, and model base, some or all of which will utilize AI methods. The data base contains the data directly relevant to the decision problem, including the values for the states of nature, courses of action, and measures of performance. The knowledge base holds problem knowledge, such as guidance for selecting decision alternatives or advice in interpreting possible outcomes.

The model base is a repository for the formal models of the decision problem and the approaches (algorithms and methodologies) for developing outcomes from the formal models. Decision-makers utilize computer and information technology to process the inputs into problem-relevant outputs. Processing will involve:

(a) *organizing problem inputs*;
(b) *structuring the decision problem* decision model;
(c) using the decision model to *simulate policies and events*;
(d) *finding the best problem solution*.

The IDSS can use knowledge drawn from the knowledge base to assist users in performing these processing tasks.

Processing will generate status reports, forecasts, recommendations, and explanations. The status reports will identify relevant states, courses of action, and measures of performance and show the current values for these problem

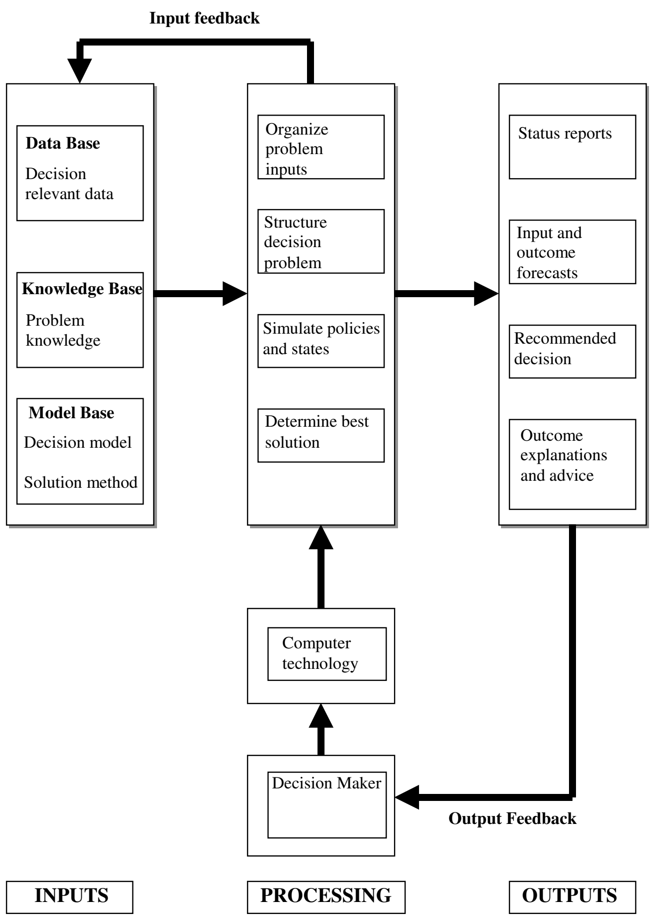

Fig. 1. Intelligent decision support system (IDSS) structure.

elements. Forecasts will report the states and actions specified in the simulations and the resulting projected values for the measures of performance. The recommendations will suggest the values for the actions that best meet the measures of performance. Explanations will justify the recommendations and offer advice on further decision making. Such advice may include suggestions on interpreting the output and guidance for examining additional problem scenarios.

Input feedback from the processing provides additional data, knowledge, and models that may be useful for future decision making. This feedback is provided dynamically to update the models and inputs in real time without external intervention. Output feedback is used to extend or revise the original analyses and evaluations.

3. Integrated design and evaluation framework for IDSS

The design and evaluation complexity of IDSS increases the requirement to justify the additional economic, human and computational efforts required when compared to traditional DSS (Messina et al., 2001). The Artificial Intelligence (AI) field, which is the main generator of design theories for intelligent systems, faces a similar problem of determining an adequate set of criteria, measures/metrics and an underlying structure/framework to assess the overall value of an IDSS (Finkelstein, 2000).

The AI evaluation approach has been traditionally focused on technical and computational performance issues (Cohen, 1991). A high human-like activity level is also recognized in the AI field as the long-term ideal characteristic for any intelligent system (Turing, 1950; French, 2000), but it is difficult to assess and offers no guidance for practical implementation. According to Simon (1987) and colleagues (Simon et al., 1987), the emergence of IDSS demands interdisciplinary research between DSS/OR and AI disciplines. In this way, valuable knowledge and wisdom concerning principles, architectures, tools, methodologies and techniques generated from both streams can be accumulated.

To integrate DSS/OR and AI evaluation criteria, our proposed evaluation schema combines several required levels of organizational (e.g. organization and user worldviews) and technical criteria (e.g. designer and builder worldviews). The framework is an alternative to previous models that were focused only on organizational effectiveness or performance system criteria for providing a complete and integrated IDSS evaluation. It is based on seminal AI research conducted by Newell and Simon (1972, 1976), Newell (1981) and Chandrasekaran (1986, 1990, 1992). The first theoretical basis is the Physical Symbol Systems (PSS) Hypothesis (Newell and Simon, 1972, 1976) that establishes that any system exhibiting intelligent actions is necessarily a PSS, and if a PSS of an adequate size and quality is developed, then it will exhibit behaviour that can be evaluated as intelligent. The second theoretical foundation is Newell (1981) enhancement to the PSS hypothesis where a third architectural level is introduced as mandatory for any AI-based architecture for intelligent systems.

The initial Symbol/Program and Logic-Circuit levels are augmented with the Knowledge Level. According to Newell (1981, p. 15) this extended framework makes a "*sharp distinction between the knowledge required to solve a problem (i.e. the knowledge level) and the processing required to bring that knowledge to bear in real time and real space (i.e. the Symbol/Program Level)*". Finally, the third theoretical support for the framework is the design theory of intelligent systems based on the notions of generic tasks (Chandrasekaran, 1986) and their refinement as a task-structure model (Chandrasekaran, 1990, 1992). This design theory postulates a more refined PSS that decomposes actions recursively into a set of problem-solving methods until specific knowledge on the lowest tasks is available to be executed (Chandrasekaran, 1990, 1992). The IDSS hypothesis (Mora et al., 2005) discussed in the Introduction is refined from the PSS Newell (1981) and Chandrasekaran's (1990, 1992) hypotheses. The result is a framework that links the upper level perspective between the impacts on decision outcomes and process (Forgionne, 1999, 2000; Phillips-Wren et al., 2004) with the AI-based lower technical view (Mora et al., 2005). This framework provides generic multiple criteria to comprehensively evaluate systems in an integrated and holistic manner. Fig. 2 (adapted from Mora et al., 2005) exhibits the four levels that link the decision-making phases and steps with the decisional services/tasks, architectural capabilities, and computational symbol/program mechanisms.

At the top Decision-making Level (organization and user worldviews), the main evaluation criteria are impacts on the process of decision making and impacts on the outcomes from using the IDSS (Forgionne, 1999). The decision process is composed of Simon's (1960) phases of intelligence, design, and choice together with implementation and learning phases.

Decisional service-task level is the next layer (user and designer worldviews), and it includes support for analysis, synthesis and hybrid service-tasks provided by the IDSS. Analysis service-tasks are classification, monitoring, interpretation and prediction. Synthesis service-tasks are configuration, scheduling, formulation and planning. Finally, hybrid service-tasks are explanation, recommendation, modification, controlling, and learning.

The third level, the Architectural-capability Level (user, designer and builder worldviews), includes the user interface (UI), the data and knowledge (D&K) component, and the processing (P) component of the IDSS architecture (Mora et al., 2005; Phillips-Wren et al., 2006b). Evaluation criteria measure the completeness of the UI, DIK and P capabilities provided respectively by the three components. The scale of completeness of the UI, DIK and P capabilities is divided into several categories (Mora et al., 2005). For instance, the UI completeness can be: (i) structured input commands and text outputs, (ii) graphics-user interface enhanced with multimedia issues, and (iii) natural language and virtual reality based user interface.

Finally, the fourth level, the Computational/program/symbol Level (designer and builder worldviews), accounts for the specific AI computational mechanisms implemented in the IDSS architectural components. Evaluation criteria are the efficacy that these mechanisms provide to the next level, e.g. the percentage of real duties done regarding the expected duties, as well as the computational efficiency of such mechanisms, e.g. the time and space complexity measures to evaluate the algorithms.

The proposed framework provides an alternative integrated evaluation view of the predictive or causal linkage between the impacts generated, the decision-making phases and steps, and the technical and functional properties owned by the different layers of an IDSS. These issues are relevant for the organization, users, designers and builders of an IDSS.

4. Evaluation of IDSS

The literature provides numerous examples to show that IDSS can improve decision making process and outcomes (Phillips-Wren and Jain, 2005; Gupta et al., 2006). To provide a recent illustration of the use of both metrics, Zhang and Pu (2006) evaluated consumer DSS with the user's cognitive effort to make and express preference in the decision (i.e. decision processes), and decision accuracy (i.e. decision outcomes). IDSS support cognitive tasks by playing an active role in aiding task performance, processing data and information to produce knowledge, and learning from experience (Linger and Burstein, 1997). They also support

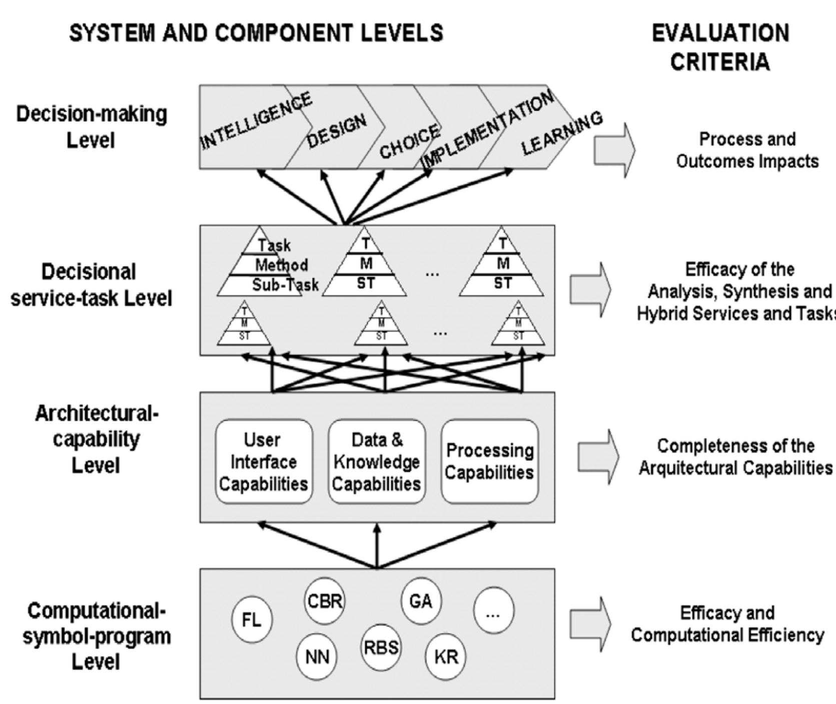

Fig. 2. Framework for design and evaluation of IDSS (Mora et al., 2005).

better decisions in terms of the outcome of the decision itself. We propose that the "decision value" of IDSS should be evaluated by the effect on both the process of, and outcome from, decision making.

Decision making in the flatter organizations and decentralized enterprises of today is increasingly distributed. Accurate and readily-available information can be provided through networked resources from a variety of sources and delivered to the decision maker in any location, and to a distributed group for collaborative decision making. Artificial intelligence enhances the potentialities of decision support systems in real management situations (Rosenthal-Sabroux and Zaraté, 1997) by, for example, bringing disparate resources together and extending support capabilities. Not only can IDSS improve outcomes, the use of AI techniques affects the process of decision making by providing the potential for real-time response, automation, personalization, sophisticated reasoning patterns, and broader information sources on which to base the decision. Intelligent systems simply do things differently than systems that do not embed intelligence. It is appropriate, then, to specifically identify system benefits originating in process, as well as outcome, support. The decision value of an IDSS, then, can be determined from a multi-criteria evaluation using the process of, and outcome from, decision making as top-level criteria.

4.1. The analytic hierarchy process

The analytic hierarchy process (AHP) is a multi-criteria method that can incorporate both qualitative and quantitative criteria into a single metric (Saaty, 1977, 1994). Multi-criteria decision making implies that a decision maker needs to identify the best course of action while considering a conflicting set of criteria. Complexity in decision making situations involves quantitative and qualitative criteria, multiple scales, and multiple comparisons. The ability to assign a preference rank for general decision making situations is needed as well as simplicity of methods (Saaty, 1986). The AHP is a plausible method that provides a logical and scientific basis for such multi-criteria decision- making (Harker, 1988) and has been widely applied to both individual and group decision making scenarios from the early 1980s (Wind and Saaty, 1980; Saaty and Vargas, 1994).

According to Saaty (1986), the AHP was founded on three design principles: (i) decomposition of the goal-value structure where a hierarchy of criteria, subcriteria, and alternatives is developed, with the number of levels determined by the problem characteristics; (ii) comparative judgements of the criteria on single pairwise comparisons of such criteria with respect to an upper criteria; and (iii) linear-based synthesis of priorities where alternatives are evaluated in pairs with respect to the criteria on the next level of the hierarchy, and criteria can be given a priority (e.g. preference) expressed as a weight in the AHP matrix.

An advantage of the AHP for our evaluation of IDSS is that the contribution of the AI methods used in the system to individual criteria can be determined. For example, it is possible to discern if system benefits from implementing an AI method derives more from process than outcome, or if an AI method contributes to a specific phase of decision making. Such information assists the system developer as well as the user to understand the precise contributions of the components of the IDSS to the overall decision value.

We have implemented the AHP previously to compare DSS and to determine their effect on the process of, and outcome from, decision making (Forgionne, 1999, 2000; Forgionne and Kohli, 2001; Phillips-Wren et al., 2004, 2006a,b). In this research we extend our previous evaluation to IDSS by using the proposed architecture in Fig. 2 to specifically determine the contribution of implemented AI methods to an IDSS. Fig. 3 illustrates an AHP model for IDSS evaluation.

The Decision Value of the IDSS is at the top of the hierarchy and depends on the decision process and outcome. Outcome describes the performance of the system in achieving the decision objective. For example, if the decision is intended to deliver decreased operating cost, then the organizational performance criterion is measured in terms of the cost decrease associated with the decision. Another possible outcome criterion shown in the figure is the growth in decision maker maturity, that is, the learning achieved by the decision maker as a result of using the IDSS. Presumably, such learning would improve the decision making skills of the user in both the current and subsequent situations (Forgionne, 1999). The improvement can be measured by the user's enhanced ability to perform decision making phases and steps, increased productivity (generating more alternatives and comparisons in a given time period), and enhanced efficiency (evaluating the same number of alternatives in a fixed time period). These improvements can be measured qualitatively (for example, self or expert ratings for decision task proficiency) and quantitatively (for example, productivity and efficiency in decision making). Process is described by the decision making phases of intelligence, design, choice, implementation and learning.

As we move down the hierarchy, there is a Decisional Service-task Level, an Architectural-Capability Level, and finally a Computational-Symbolic Program Level with AI computational mechanisms as alternatives. The evaluator may choose to modify the AHP model to tailor the desired criteria for a specific IDSS. We have shown one possible implementation in Fig. 3 along with potential alternative AI methods such as a genetic algorithm, intelligent agents, a neural net, a hybrid system, or none meaning that no intelligence is embedded. In the AHP model, the alternatives are evaluated in pairs with respect to the three elements in the Architectural-Capability Level: user interface, data & knowledge capabilities, and processing capabilities.

As an illustration, the user interface capability may need to be personalized for each individual user. Then, in pairs,

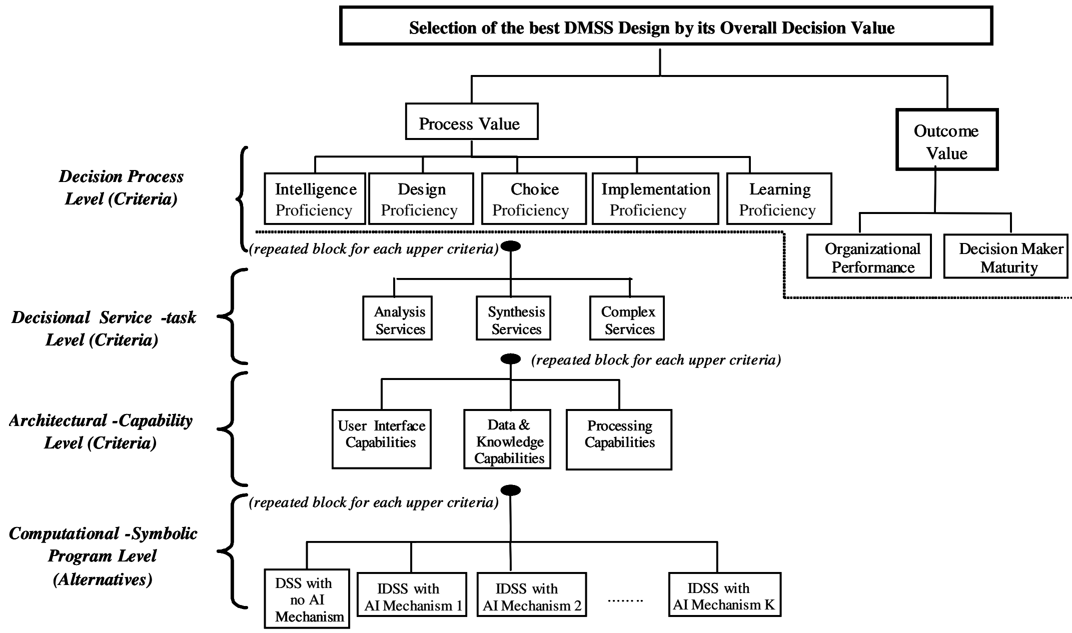

Fig. 3. AHP model for IDSS evaluation.

the alternatives are compared with respect to how well they provide personalization in the user interface. The user might indicate that agents are much better than a neural network in providing personalization in the user interface, and this judgment is expressed in the AHP as a relative rating. An eigenvalue computation is utilized to reconcile the pairwise judgments, and a ranking of alternatives on the specific criteria is produced using the judgments and the weighting of the criteria. The AHP then proceeds by evaluating the user interface, data and knowledge capabilities, and processing capabilities with respect to the three types of decisional services: analysis, synthesis or complex services. Numeric ranking values are produced for the alternatives using the criteria weights provided by the evaluator. The elements of the Decisional Service-task Level are similarly evaluated with respect to the Decision Process Level: intelligence, design, choice, implementation, and learning. Finally, a numeric ranking of the alternatives is computed for outcome, and these ratings are combined with the overall rating calculated for process to provide an overall ranking of the alternatives with respect to the decision value, the highest level in the AHP model. The ranking at the top level indicates which alternative, i.e. what AI-based mechanism in this case, has the best decision value, and a highest ranking can be interpreted as a selection of the best design for the IDSS. In addition, the precise contributions of each AI method to each criterion in the hierarchy can be determined.

4.2. Description of application

Intelligent decision support systems have been developed and evaluated for significant real-world applications, and we have selected one such recent application from the literature by Quintero et al. (2005) to illustrate our approach to design and evaluation of IDSS. We briefly describe the IDSS and then apply our proposed evaluation architecture to suggest the impact of AI methods in the system.

Quintero et al. (2005) described an IDSS that coordinates management of urban infrastructures, such as sewerage and waterworks, to decrease the human and economic resources needed to respond to an event or need while increasing the quality of service. Decisions are complex and involve restoration of quality service in the event of a disruption, management of interrelated resources when more than one service is needed, and preventive maintenance and rehabilitation of existing services. In many (if not all) cities, decisions about an action or lack of action involving infrastructure departments are made without consultation among all stakeholders. A major challenge is the integration of proprietary systems developed for individual applications. Data cannot be transferred easily from one application to another, limiting the ability for decision making that impacts more than one infrastructure department. As the population grows and the number of requests for service increases, infrastructure services are expected to be severely stressed by increasing demand so that decisions are not optimal with the current staffing. The authors point to literature suggesting that meeting future challenges in the management of urban infrastructures will be difficult without the introduction of new technologies, and they propose an IDSS to provide a coordinated effort for municipal services.

Their system is consistent with our concept of an IDSS; it is described as supporting decision making by a knowledgeable human user or users who need(s) to make a specific, identified decision that is unstructured or semi-structured.

The user is thus part of the system, and the automated system supports some or all of the tasks in the decision making process consisting of intelligence, design, choice, implementation or learning. To do so, the IDSS is flexible, interactive, incorporates the decision maker's insights into the decision making process, provides a user-friendly interface, allows what-if analysis, and supports analysis valuable to the decision maker such as tradeoffs in the decision. Intelligence in embedded through AI methods that improve the system performance and outcomes.

The system by Quintero et al. (2005) is based on case-based reasoning (CBR), an AI method that develops solutions to new problems based on solutions of similar problems addressed in the past. They describe a four-step process from the literature consisting of retrieve, reuse, revise, and retain. The system is cooperative and composed of a set of particular urban systems such as a Sewerage System or Waterworks System integrated via a global planning and coordination system. The integrated system addresses topics such as routine daily operation, preventive maintenance, monitoring of performance, and selection of alternatives to improve response to demands.

The IDSS utilizes intelligent agents (IA) in a multi-agent system described as containing four elements: agents with characteristics such as autonomy and pro-activeness; mobility for real-time response; tasks to be accomplished; and, urban infrastructures together with their information. Agents coordinate, cooperate, and communicate using ontology to provide a common vocabulary and a knowledge base to provide the state of the world. Control is both global and local in order to determine task priority and to determine which infrastructure departments are needed to accomplish a task. Agents also act as the voice of citizens with, for example, a complaint agent. The agents interact to identify and solve problems in a complex environment.

4.3. Evaluation of application

Quintero et al.'s IDSS (2005) can be evaluated using our AHP model of the proposed framework to determine the contribution of IA to the components of the IDSS as well as to the process of, and outcomes from, decision making. To illustrate our concept, we have used proposed values for the comparisons and weights. Two alternatives are compared, a DSS with no AI method, and the IDSS with CBR and IA. The proposed evaluation model is shown in Fig. 4.

We have reduced the evaluation model to reflect criteria that we propose as important for the actual IDSS based on the research presented. The paper discusses the outcome in terms of the decrease in redundant complaints and the precision of decision making. Process outcomes are discussed in terms of the user interface, data and knowledge capabilities, and processing capabilities–the elements in our Architectural-Capability Level. The IDSS is capable of both analysis and synthesis, and we represent these services on the Decisional Service-task Level. The phases of decision making that are supported are intelligence, design, choice and learning. During intelligence, the IDSS searches for information from all of the infrastructure departments as well as contributing stored information about the infrastructures. The system also has access to previous solutions

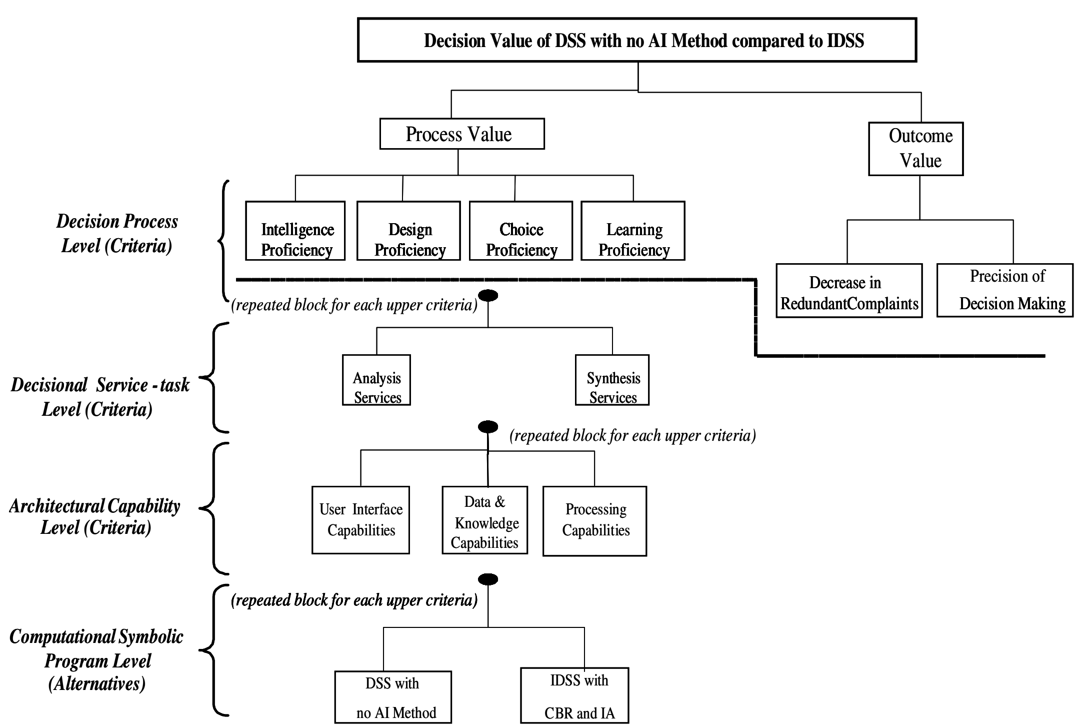

Fig. 4. Proposed evaluation model for Quintero et al. (2005) IDSS.

and expert opinion. During design, it determines which data are relevant to prioritize tasks and arrive at a solution. During choice, the user is able to interact with the system using feedback loops for further analysis and to make a final selection of which infrastructure departments to deploy. We have included learning, since the IDSS not only stores experts' original cases, but also utilizes adapted cases in its databases.

Having chosen the evaluation criteria, we proceed to a proposed weighting of the criteria as shown in Table 1. The values utilized can easily be modified to reflect different priorities of different users or designers. To estimate the overall decision value, the weights of the criteria in the AHP model are used together with the values assigned on the bottom level for either 'DSS with no AI method' or 'IDSS with CBR and IA'.

Once the weights associated with the criteria are known, the evaluation analysis proceeds with the initial values of the alternatives at the bottom level of the AHP model. The alternatives, 'DSS with no AI method' and 'IDSS with CBR and IA', are compared with respect to how well they perform for User Interface, D&K, and Processing Capabilities. For comparison we assume a hypothetical DSS with no AI method, so that the comparison determines the value of the IA methods (CBR and IA in this case) in the decision process and outcome. Since both systems are decision making support systems, we assume that both systems have a user interface, can incorporate the decision maker's own insights, are interactive, and provide what-if analysis (Quintero et al., 2005). The IDSS brings together "human judgement and computerized information providing support to decision makers primarily in the analysis of poorly or unstructured situations" (Quintero et al., 2005). We have assumed that the urban infrastructures office is staffed with knowledgeable people, some of whom are experts. The values we entered at the bottom level are 0.60/0.40 for the User Interface, indicating that the DSS with no AI method provides a somewhat simpler User Interface; 0.40/0.60 for D&K, indicating that Data and Knowledge are somewhat better in the IDSS; and, 0.20/0.80 for Processing, indicating that Processing is much better with the IDSS since it suggests a decision or set of actions based on more data and expert opinion. These values appear to be consistent with the descriptions provided by the authors of the study, although different values can easily be considered.

A summary of the evaluation of the 'DSS with no AI method' compared to 'IDSS with CBR and IA' is shown in Fig. 5. The overall decision value of the IDSS (decision value of 0.589) is higher than that of a DSS using no AI method (decision value of 0.411), indicating that use of the IDSS improves decision making. The IDSS primarily improves the process of decision making (.381 compared to .619), and this is consistent with the actual observed results of knowledge sharing and increased levels of automation (Quintero et al., 2005). The outcome of decision making is improved as well (.431 compared to .569), with both better precision (.374 compared to .626) and decrease in redundant complaints (.455 compared to .545). These results are consistent with the observed data from using

Table 1
Weights assigned for the criteria in the AHP model

Level	Criteria by level	Weights	Comments
Decision-making	[Process/outcome to decision value]	[0.40, 0.60]	User considers the outcome more important than the process (e.g. 60% for outcomes and 40% for the process)
	[Decrease in redundant complaints/precision of decision making to Outcome]	[0.70, 0.30]	User considers the decrease in redundant complaints more important than the precision of decision making (e.g. 70% vs. 30%)
	[Intelligence/design/choice/learning proficiency to process]	[0.20, 0.50, 0.20, 0.10]	The user considers the design of the infrastructure solution more important than the other phases
Decisional service-task	[Analysis/synthesis to intelligence]	[0.80, 0.20]	For the intelligence phase, the user considers the support provided by analysis to be most important
	[Analysis/synthesis to design]	[0.10, 0.90]	For the design phase, the user considers synthesis to be most important
	[Analysis/synthesis to choice]	[0.50, 0.50]	For the choice phase, the user considers both analysis and synthesis of equal importance
	[Analysis/synthesis to learning]	[0.30, 0.70]	For the learning phase, the user considers synthesis to be more important
	[Analysis/synthesis to decrease in redundant complaints]	[0.75, 0.25]	The user considers analysis to be more important in the decrease in redundant complaints
	[Analysis/synthesis to precision of decision making]	[0.30, 0.70]	The user considers synthesis to be more important in the precision of decision making
Architectural-capability	[User interface/D&K/processing to analysis services]	[0.10, 0.45, 0.45]	The user considers D&K and processing to be important for analysis
	[User interface/D&K/processing to synthesis services]	[0.10, 0.20, 0.70]	The user considers processing to be most important for synthesis

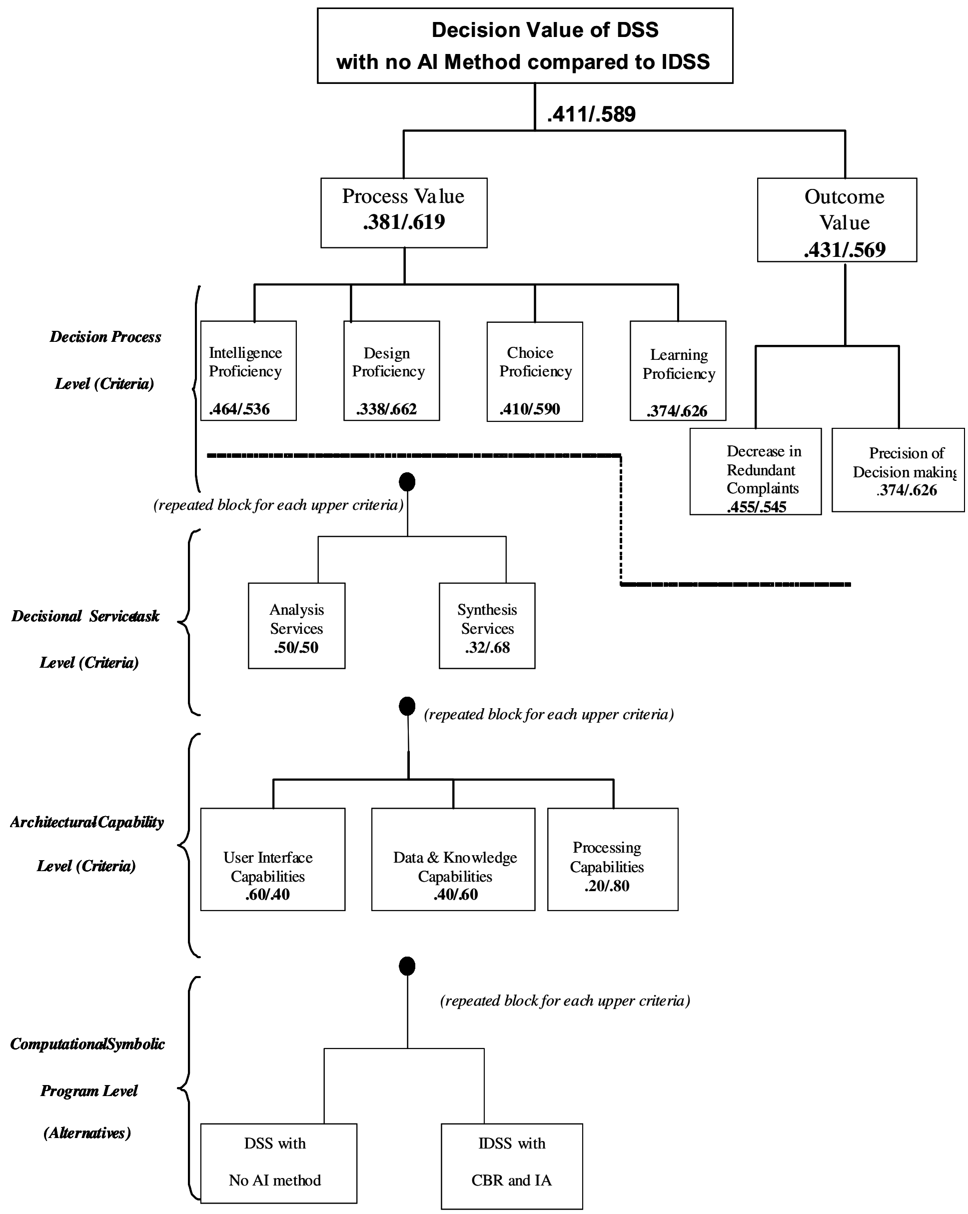

Fig. 5. Evaluation of IDSS compared to DSS with no AI method. The pair value *X*/*Y* means that the *X* value has been calculated for the DSS and the *Y* value for the IDSS.

the IDSS in the city of Verdum for the merging of lighting and embellishment complaints (Quintero et al., 2005); the system found three similarities out of 33 for embellishment, and one out of 18 for lighting. Although data are not provided explicitly for precision, the IDSS uses expert's original cases and provides a second layer of already adapted cases. This is consistent with the results in Fig. 5 on the Decision Process Level in which Design Proficiency and Learning Proficiency are the primary enhancements with the IDSS (.338 compared to .662, and .374 compared to.626, respectively). We see that both systems are evaluated to be the same on Analysis Services (.50/.50), with the advantage coming from Synthesis Services (.32/.68). According to Buede (1986), a useful decision-making tool/method should correctly discriminate between alternatives so that a decision-maker can select one. Our proposed architecture appears to be consistent with observations by Quintero et al. (2005) about their real-world IDSS, and we suggest that the evaluation schema provides insight into the contributions of the IDSS to specific tasks in that framework.

5. Conclusions

Like all systems designed to support decision making, IDSS must provide decision value to the user. Previously, there has not been a complete, integrated, systematic, and documentable methodology to measure such value. The framework proposed in Fig. 2 offers such a methodology. It is multiple criteria, systematic, user-centered, and formal. The framework also offers a methodology to trace the source of the decision value through process, outcome, service support, architectural components, and down to the specific intelligent mechanism to be used in the design of an IDSS.

The proposed methodology is the modified labelling and backtracking algorithm illustrated in Table 1. Such support tracing offers a detailed, systematic, and logically justified mechanism to examine system design and development from a user-centered perspective. In particular, the methodology provides the designer and developer specific guidance on the intelligent tools most useful for a specific user with a particular decision problem based on their preferences. Moreover, such support can be rendered dynamically and in real time by incorporating adaptive design tools within the designed IDSS.

The application case illustrated in this paper should be taken as a sample and initial effort to demonstrate the methodological design and evaluation potential capabilities of the proposed framework. Further theoretical and empirical research is suggested to enhance and validate the proposed framework through its application to other IDSS in varying contexts.

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