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Dynamic interaction in knowledge based systems: An exploratory investigation and empirical evaluation

Brandon A. Beemer *, Dawn G. Gregg

University of Colorado at Denver, United States

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ABSTRACT

In response to the need for knowledge based support in unstructured domains, researchers and practitioners have begun developing systems that mesh the traditional attributes of knowledge based systems (KBS) and decision support system (DSS). One such attribute being applied to KBS is dynamic interaction. In an effort to provide a mechanism that will enable researchers to quantify this system attribute, and enable practitioners to prescribe the needed aspects of dynamic interaction in a specific application, a measurement scale was derived from previous literature. Control theory was used to provide the theoretical underpinnings of dynamic interaction and to identify its conceptual substrata. A pretest and exploratory study was conducted to refine the derived scale items, and then a confirmatory study was conducted to evaluate the nomological validity of the measurement scale.

1. Introduction

Information Systems (IS) literature contains two main system architectures designed for decision support: knowledge based systems (KBS) and decision support systems (DSS). KBS have been defined as a system that uses human knowledge captured in a computer to solve a problem that ordinarily needs human expertise and have applications in virtually every field of knowledge [6]. KBS are designed to deal with complex problems in narrow, well-defined problem domains. If a human expert can specify the steps and reasoning by which a problem may be solved, then a KBS can be created to solve the same problem [21]. The architectural design of KBS are very different from traditional systems because the problems they are designed to solve have no algorithmic solution; instead, they utilize codified heuristics or decision-making rules of thumb which have been extracted from the domain expert(s), to make inferences and determine a satisfactory solution [7,37]. For unstructured decision domains, DSS are developed, which are collaborative systems that use various types of formulas and algorithms to synthesize information from various data sources [6]. The architectural design of DSS differs significantly from KBS's heuristics approach, instead they are designed to interactively tract with the user's non-linear cognition process in unstructured decision domains [23,26,49].

A functional gap has existed between KBS's support of structured decisions and DSS's support of unstructured decisions [6]. Despite this, the need to apply knowledge to unstructured domains exists, and recently system developers have begun meshing the traditional characteristics of these two system architectures to provide knowledge based support of unstructured decisions. This is being accomplished by incorporating dynamic interaction (which is traditionally a DSS trait) into KBS [18,28,53]. Fig. 1 provides an illustration of emerging system designs that are bridging the described functional gap between knowledge based systems and decision support systems (e.g. iterative expert systems, advisory systems, web 2.0 mash-ups).

As Fig. 1 illustrates, a common feature shared by these three systems is dynamic interaction [7,28,53]. Iterative expert systems closely resemble traditional expert systems but include the added functionality of an iterative decision process that allows the user to revisit and revise their inputs and consider alternative solutions [28]. Advisory systems are also driven by an iterative system process, but unlike iterative expert systems which are typically rule-based, advisory systems couple rule-based reasoning with other forms of logic such as case-based reasoning [7]. Another type of system that is bridging the gap between knowledge based systems and decision support systems is Web 2.0 Mash-ups, which provide an enhanced interactive web experience that allow a variety of users to share in the generation, organization, distribution, and utilization of knowledge [53].

Generally speaking, when knowledge based systems are applied to unstructured domains they tend to experience low user acceptance resulting from mistrust of the system because of its inability to justify solutions [19]. There are two main schools of thought addressing this low user acceptance rate. The first focuses on developing more robust explanation facilities to justify the system's solution in unstructured domains [5]. The second declares that "the need for interaction between knowledge based systems (KBS) and the user has increased, mainly, to enhance the acceptability of the reasoning process and of the solutions proposed by the KBS" [19, pg. 1]. Through dynamic interaction with the

* Corresponding author.
E-mail addresses: Brandon.Beemer@email.cudenver.edu (B.A. Beemer), Dawn.Gregg@ucdenver.edu (D.G. Gregg).

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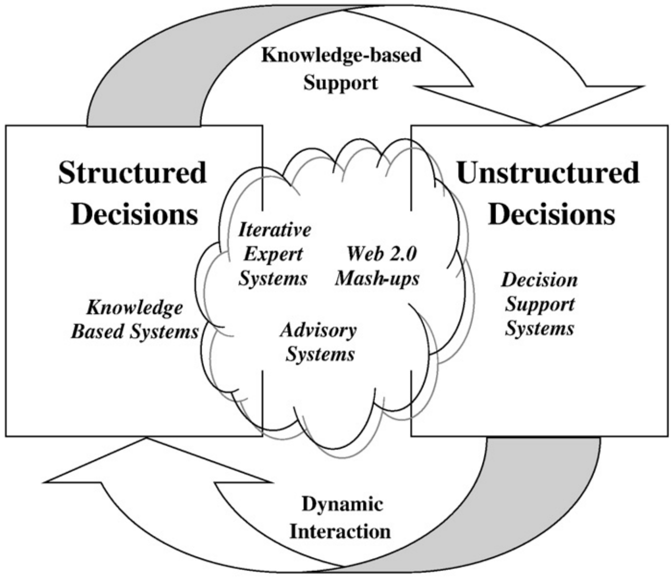

Fig. 1. Dynamic interaction bridges gap between KBS and DSS.

user, KBS are able to tract with the user's iterative cognition process in solving unstructured decision and involve the user's opinion in the system's logic, which gives them a sense of ownership (and ultimately trust) in the solution [26,38].

The purpose of this study is to derive a measurement scale to quantify dynamic interaction in knowledge based systems. It measures dynamic interaction as a construct that is perceived by the user because of the positive or negative influence a user's initial attitude towards the system may have on the actual dynamic interaction that takes place during system use. A review of system control theory literature is conducted which provides the theoretical underpinnings for the substrata and nomological model of dynamic interaction. Upon this foundation a multi-item measurement scale is derived for dynamic interaction which is then evaluated in an exploratory and confirmatory study. Lastly a discussion is presented that covers the implications of this study on future research.

2. Theoretical background

Dynamic interaction is neither a new concept nor is it limited to the decision support architectures previously discussed, in fact it has been around for several decades in artificial intelligence literature. In the 1990s the World Wide Web began to take on dynamic characteristics with database driven web applications that serve custom web pages designed to meet specific criteria and interests of unique user [25]. Web applications then evolved into virtual working environments and various studies evaluated groupware architectures in terms of their ability to synthesize and support the dynamic interaction between colleagues and teacher/students in distance education [31]. Most recently, dynamic interaction is being expanded to make systems increasingly proactive with technologies like AJAX (Asynchronous JavaScript and XML) which brings browser-based interaction much closer to application-based interaction [36,44,46]. Despite the popularity of dynamic interaction as a system attribute, IS literature lacks a measure to quantify the role of this construct within the information system nomological net. To address this need, the focus of this paper is to derive such a measurement for dynamic interaction.

Dynamic interaction's underpinnings are found in system control theory, which spans many academic disciplines ranging from engineering to economics and is primarily focused with influencing the behavior of dynamic systems [30]. Specifically stated, "control theory is the area of application-oriented mathematics that deals with the basic principles underlying the analysis and design of control systems. To control an object means to influence its behavior so as to achieve a desired goal" [48, pg. 1]. The majority of control theory applications incorporate some variation of a feedback loop; as Fig. 2 illustrates a feedback loop has 3 general phases: A) input values, B) process input and calculate output, C) evaluate output, if necessary iterate back to step A) and adjust input values [43].

A common application of control feedback loops is machine learning which includes but is not limited to autonomous robots, fuzzy logic, intelligent systems, neural networks, and database autonomics. For example, database autonomics has become more popular as databases have become increasingly large and complex and the human resource cost to administer these databases has also grown. To help ease the cost of ownership of the large databases, researchers have begun developing self managing databases (ADBMS) that automatically configure and manage its resources [17]. Essentially an ADBMS is a control feedback loop that oversees the database and collects and analyzes statistics, determines whether performance is satisfactory or not, and then takes appropriate action to resolve performance issues if they exist [35].

The control feedback loop is also being applied in the context of dynamic KBS related to the brain-computer interaction subset of machine learning. While there is no physical connection involved, the KBS includes the user's cognition process in developing a solution through dynamic interaction. KBS can be effective in supporting unstructured decisions when they are designed with feedback loops that allow the user to influence the behavior of the system as to achieve the desired solution by evaluating alternative solutions [48]. A good example of knowledge based support being applied to unstructured decisions via dynamic interaction would be an Iterative Expert System built for solving shipment consolidation problems. Lau and Tsui [28] developed such a system that adopted rule-based reasoning to provide expert advice for cargo allocation, and included an iterative improvement mechanism that undertakes different outcomes until an optimal solution is found.

3. Hypothesis model

Examining the predictive ability of a measurement scale and its nomological validity requires identifying the constructs within a nomological network of consequent variables [9]. Fig. 3 illustrates the hypothesized nomological network for dynamic interaction, which has been constructed from prior literature, and serves as the research model for this study. The hypothesized consequential constructs of dynamic interaction are Perceived Reliability (trust in the predictions made), Perceived Usefulness, and Behavioral Intention to Use. The hypothesized relationship between dynamic interaction and these consequential constructs are discussed below.

The primary conceptualization of DSS/KBS trust is based on the assumption that users' generally adapt their trust levels to accommodate different levels of recommendation quality. That is, the more reliably the system is in providing appropriate decision recommendations, the higher the level of trust the user will have in the system. For

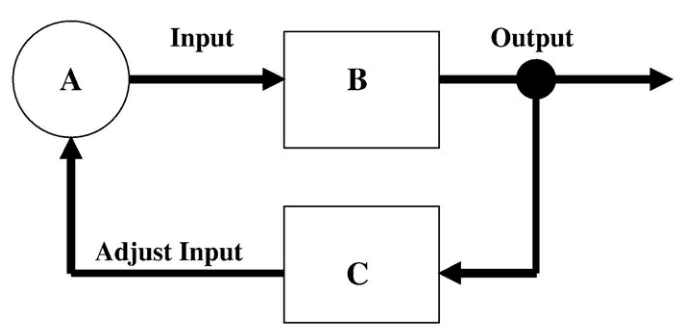

Fig. 2. Control Theory Feedback Loop, derived from [43].