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Artificial Intelligence, Management and Organizations

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Abstract:

In recent years, many companies have used artificial intelligence (AI), which includes neural networks, expert systems, and voice recognition systems. However, managers and developers have very little understanding of how management and organizations influence or are influenced by technology.
This article discusses the interaction of AI, management, and organizations using specific examples from practice and research, and provides some methodological approaches and theoretical models to describe and study those interactions and provide directions for future research.

Introduction

Artificial intelligence (AI) has moved from research laboratories to business. Recent surveys show that a large number of companies have developed AI applications in the past two years, and the growth of applications continues today. (Kommel, 1990; Fransett, 1991).

Many of these applications are stand-alone systems, but others are integrated with traditional information systems (IS), such as data processing and management information systems. Most applications are knowledge-based expert systems (ES), but there are a growing number of applications of other AI technologies, such as neural networks, knowledge-based planning and scheduling systems, speech synthesis systems, and voice recognition systems. (Feigenbaum et al., 1988; Andrews, 1989; Business Week, 1992; (Murphy and Brown, 1992).

Despite the proliferation of technology, managers and developers have little knowledge of the practical issues related to the interaction of AI, management and organizations. This is an important issue, since the success of an AI system depends on solving a variety of technical, managerial and organizational problems.

However, academic research is limited. O'Leary and Turban (1987) reviewed the theoretical foundations for assessing the impact of AI on organizations. Some researchers have discussed the organizational impact

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of ES by conducting an analysis of a single system (e.g., Sowikal, 1990) or by comparing a group of systems (e.g., O'Keefe et al., 1993).

Others have analyzed the ES implementation process to develop an understanding of the "critical success factors" and to provide managers with guidelines for achieving successful implementation. (Irgan et al., 1990; Meyer and Curley, 1991; (Duchesse and O'Keefe, 1992).

The number of studies on the interaction of AI, management, and organizations is smaller than for other IS, for at least two reasons. First, compared to traditional IS, most AI applications are new (mostly in the last 5–10 years), which limits our collective knowledge about their organizational impact. Second, in the early to mid-1980s, technical development issues (e.g., knowledge acquisition, system programming, and validation) dominated broader nontechnical organizational issues. Thus, the interaction of AI, management, and organizations is a nascent field of research. The purpose of this article is to discuss the nature of the interaction, review the relevant research design, and suggest some related research opportunities. The next section provides a general framework for discussing the interaction of AI, management, and organizations. We use specific examples from practice and research to illustrate parts of the framework.

Then, approaches we summarize the prominent methodological and theoretical models for analyzing AI, management, and organizations, respectively. Finally, we provide directions for future research.

AI, Management, and Organizations

A framework for discussing the interaction of AI, management, and organizations is shown in Figure 1. Although organizations and management clearly interact directly (Orlikowski, 1992), we emphasize issues that are directly related to AI. Reassignment of Decision-Making Responsibility Artificial intelligence has the ability to change ownership and responsibility for decision-making.

An example of this is American Express Authorization Assistant, an ES that handles most of the authorization requests made with American Express cards. This system allowed American Express to automate many of its credit responsibilities and eliminate ownership of decisions.

Organizations are characterized by their institutional characteristics, including structure, size, and function. These factors provide different contexts for the development and implementation of AI and reflect the positive or negative consequences of this technology.

Management plays an important role in the adoption and support of the technology (e.g., through resource provision), and may use it as a business strategy. Artificial intelligence is not the same in all situations as a product; it shapes it and is shaped by the other two components of the framework.

Impact of AI on Organizations

Some of the impacts of AI on organizations include: shifting power, reallocating decision-making responsibility; reducing costs and increasing services; and shifting and retrenchment. Here we review these obvious impacts and recognize that there are many more.

Shifting Power

The possibility of shifting power within an organization due to changes in ownership and control of knowledge has been discussed (O'Leary and Turban, 1987). For example, the Screener Call PC, developed by Eastman Kodak in the late 1980s, is an ES that diagnoses common problems with personal computers, including display, disk drive, and communication problems.

This allowed office personnel to assist users over the telephone, eliminating the need for some on-site service calls by technical specialists. Implementation of this system showed that employees with the system solved more problems than technicians without it, and that technicians engaged in unnecessary tangential thinking. This system gave employees the ability to take on the role of more skilled technicians and reduce the power of the next group (Duchesse and O'Keefe, 1993).

Reassigning Decision-Making Responsibility.

AI has the ability to shift ownership and responsibility for decision-making. An example of this is American Express's Authorization Assistant, an ES that handles the majority of authorization requests made with American Express cards.

This system allowed American Express to automate many of its credit authorization responsibilities and remove ownership of the decision from authorization employees. In the area of personal loan and credit analysis, neural networks are now used by many large credit card companies, including Citibank and General Electric Financial Services, to make some of their credit-granting decisions. Corporate secrecy means that details about these systems and their use are scarce.

Reduce Costs and Increase Service.

Implementing AI systems can help reduce costs, increase the service provided by an organization, or do both. In addition to automating authorization decisions, the Authorizer Assistant has allowed American Express to significantly reduce labor costs and better manage the issuance of cards without fixed limits.

This type of business benefit is already being praised by management more than the usual benefits (including reduced decision time, better use of dedicated time, and knowledge codification).

Relocation and Downsizing.

Artificial intelligence can help with the maintenance costs of an organization's software, often requiring a dedicated support staff. While this is the case for other IS, given the dynamic nature of knowledge, the cost of maintaining and improving AI applications can exceed that of traditional IS. XCON was rumored to have 50 full-time employees dedicated to its maintenance. In a major downsizing, in 1992 T&AT announced that it would be installing a new AI-based speech recognition system that would eliminate up to a third of its 18,000 operators. (Wall Street Journal, March 4, 1992).

This is the first example of a large job loss due to the implementation of AI. These examples show that AI can increase the number of employees and reduce the amount of direct labor, and usually leads to both. The Impact of Organizations on AI Organizational characteristics, including job design, process design, and culture, affect the deployment of AI systems.

For example, O'Leary and Watkins (1992) show that specific organizational characteristics (such as size, technological awareness, and IS budget) affect the adoption of ES. A system may be implemented or used differently in the context of different structures and cultures.

We consider this issue from several perspectives: user motivations for adopting AI; external organizations; organizational structure; and organizational support We know that we are only examining the surface of a complex issue (perhaps even less than the impact of AI on organizations is understood).

User Incentives for AI Adoption.

As with other types of IS, AI systems are unlikely to be used if users are not motivated to adopt them. The Commercial Loan Analysis Support System (CLASS) supports commercial loan officers in assessing a company's financial health, recommending loan contracts, and documenting commercial loan analysis. Although the system had technical expertise, it provided few incentives for loan officers to use the system.

CLASS required loan officers to use computers to solve their problems, which was inconsistent with the company's culture that prohibited the use of computers in the loan office. Furthermore, loan officers never created a personal stake in the system.

The system validated their opinions but never represented a personal interest to loan officers, even though they agreed that the system would help them avoid bad loans. These factors had a significant impact on their implicit decision not to use the system (Duchess and O'Keefe, 1992).

External Organization

As AI systems become larger and more visible, the opportunity for external organizations (including unions and regulatory agencies) to influence their development and deployment increases. The T&AT speech recognition system, introduced above, provides a rare example of how an external organization can influence the implementation of AI.

T&AT announced the implementation of its speech recognition system during contract negotiations with the Communications Workers of America (CWA) union. The system became an important platform in labor relations and negotiations. Eventually, the CWA negotiated an agreement that gave T&AT operators, who were replaced by the new system, "influence" in other jobs at T&AT (Wall Street Journal, July 3, 1992).

Organizational Structure

Drucker (1988) suggests that organizations are moving away from the classic stovepipe structure. With the emergence of self-managing teams, distributed responsibilities, and decentralized structures, there are new opportunities for AI, as this technology facilitates decentralized decision-making, more consistent decision-making, and greater reliability in decision-making processes.

Mrs. Fields' company uses ES to help manage its network of retail stores (Pancari et al., 1991). These systems are used to leverage Debbie Fields' (founder) influence in the stores, allowing Fields' managers to run the stores in the same way she ran her first store 10 years earlier.

Organizational Support

Users, immediate management, and their subordinate support staff have the power to advance or inhibit AI systems. Any of these may reduce operational use by limiting the number of users, changing the composition of the target group, conserving resources, or limiting the area affected within the organization.

Ducasse and O'Keefe (1993) found that organizational support, as measured by the rotation of user needs, adequate computer resources, and general community support, has a positive effect on operational use.

Impact of AI on Management

Focus on ES Currently, ES that lead to product or service differentiation or cost reduction have a direct impact on management strategies for gaining competitive advantage. By using some ES, management can take offensive or defensive actions to counter competitive forces and create a defensible position for the company. Strategies need not be limited to products alone, but can also include other actions such as developing a trained workforce.

Products

Perhaps the most common examples of using AI for product differentiation are expert configuration systems that take product specifications or descriptions and produce parts lists and instructions for putting the product together. Much has been written about the origin of such systems, XCON.

Similar examples outside the computer industry include the Carrier EXPERT system, which produces designs for large, complex air-conditioning units for multi-story buildings, and General Electric's Computer-Aided Request Engineering (CARE) system, which allows salespeople to search a database of electric motors that meet customer specifications, or automatically design a new motor if one does not exist.

These systems result in fewer engineering errors, lower base costs, and reduced cycle times. However, the major impact is the company's ability to provide (in other words, digitally) card production to its customers, who no longer have to choose from a model with multiple options because they can specify what they want and have it created for them.

Workforce

For many service organizations, retaining and effectively utilizing a skilled workforce is critical to profitability. For example, public accounting firms must disseminate changes in tax and accounting information to each of the accountants who perform those activities. Coopers ExperTax and Lybrand's system guides accountants through the information gathering process and helps them explain the differences between statutory and effective (or computed) tax rates (Schapelberg and Graham, 1989).

The system notes relevant issues, describes the significance of the requested information, and analyzes it to identify critical issues for audit and tax managers. Willingham and Rebar (1988) consider auditor training to be one of the main benefits of ES. These types of systems can reduce labor costs and increase accuracy (especially when the customer has little marketing information to differentiate between providers).

Management's Impact on Artificial Intelligence

Management plays a key role in the adoption of AI in an organization and its successful implementation. The two main ways management can exert influence are: acting as a support for an AI system and providing the resources to implement it.

Support

One of the primary issues in implementing AI systems seems to be the need for support to promote the use of AI. (Hays-Roth et al., 1983). Being supportive goes beyond verbal support of the system, it includes a willingness to actively support the technology and make it a high priority within the organization. Ducasse and O'Keefe (1993) found that top management support and manager acceptance are important for the success of ES implementation and favorably influence users' perceptions of management support and operational use.

Provision of resources

O'Leary and Watkins (1992) found that organizational pressure to adopt ES, management support, and adequate funding for technology were positively related to ES adoption. Ducasse and O'Keefe (1992) found that management support includes providing people, time, and money. By having the initial source of support, allocating resources, and giving at least as much importance to implementation as other business activities, management can have a significant positive impact on the successful deployment of AI.

Artificial Intelligence and Other Information Technologies

Although AI is considered a stand-alone technology, it is an integral component of IS assets. IS planning attempts to align computer-based systems with the needs of the organization. Top-down approaches begin with business objectives and derive desirable architectures and structures to support the goals that encompass all aspects of computing, and determine (at least to some extent) the nature and number of AI systems on the employee's desk.

Through IS planning, the organization chooses what AI systems it wants to build, determines the budget level for them, and how they will be integrated with existing databases and The planned, data entry systems, reporting systems, and decision support technologies determine. Organizations that have aggressive programs that include AI will deploy this technology throughout their business.

Ultimately, the contribution of AI systems is likely to be a function of how they integrate and interface with other hardware, software, policies, procedures, and organizational arrangements that collectively form an improved business process. Therefore, AI systems will be components of larger business systems with cost and profit confounding issues.

The two dominant approaches to studying the interaction of AI, management, and organizations are case studies (single and multiple) and empirical studies. Most case studies are about successful applications. There are a few cases of failures that may be more important to analyze than successes. Case studies provide both practical insights and a basis for developing theories that can ultimately be tested empirically.

Discussion and Conclusion

To date, single-case analysis has been the most common approach used to study artificial intelligence, management, and organizations. There are a number of published studies that focus on a single successful case study. For example, Oswieciel (1990) described the organizational impact of XCON in digital.

He found that using XCON increased the organization's information processing capacity, the local execution system changed the configuration task, and the system directly supported the digital product strategy. In contrast, Reitman and Shim (1993) used a case study to discuss the customer and vendor perspectives on the failed implementation of Palladian software management consulting.

With respect to the customer, they found that companies attempting to implement an ES for financial planning needed to have a sufficient understanding of the strategic or organizational problems that the system was supposed to address.

In addition, developing an advanced commercial ES for strategic financial planning entailed technical and market risks for the vendor. The newer the system, the broader its scope, and the greater the discrepancy between the task interactions supported by the system and the actual customer processes, the greater the risks.

The failure cases are noteworthy because they provide a different perspective. They sometimes include factors that are also present in the analysis of successful AI implementations, questioning the importance of these factors as contributing to success. Moreover, they are very rare: in general, managers, project leaders, or developers are reluctant to admit and discuss failure.

To analyze the success or failure of ES implementation, Ducasse and O'Keefe (1993) used a multiple-case design in which each case serves as a separate experiment that confirms or refutes the inferences drawn from the group of cases. After analyzing each case separately, the method organizes the cases into success and failure categories to facilitate the search for patterns. This search focuses on identifying within-group similarities among the successful and less successful categories as well as between-group differences. The cases are then reexamined to determine whether they support the propositions derived from the search process. The multiple-case design is useful for identifying propositions or constructs for theory building. It provides a good description of the inductive theory method and has been successfully applied elsewhere (Eisenhardt, 1989).

Empirical Studies

There are few empirical studies on AI, management, and organizations, and the existing studies focus on where and how the technology is used in the market. Generally, AI consulting firms and vendors conduct surveys to determine the extent of AI development and use in organizations, and thus follow quite limited research perspectives. Here we briefly summarize two typical academic studies. Pickett and Case (1990) surveyed R&D professionals about AILES applications in R&D.

The survey found that companies that have the resources to deploy the technology do so very cautiously, viewing it as a means to capture irreplaceable expertise and improve control over complex systems. In addition, respondents identified several barriers to the use of AI and ES, including managing the value of the technology, developing a knowledge base, and lack of appropriate development tools. The small sample size (33 responses) limits the value of the study.

Dokidis and Paul (1990) conducted an empirical analysis of the use of AI techniques among members of the British Operations Research Association (OR). The findings of this study include: Professional and organizational motivation is the main reason for using AI.

Other departments within an organization are close to OR departments for AI development, which may explain the success of some OR departments in seemingly innovative ways. It shows that ES is the main technique of AI because of its cost-effectiveness.

To date, empirical studies have been descriptive rather than inferential in nature. Quantitative studies are conceived as well-defined research projects to test theoretical propositions and models that emerge from a careful analysis of existing literature or case studies. However, the excessive cost, time, and difficulty in obtaining a representative sample are strong limitations to conducting an empirical study.

Theoretical Models for Analysis

There are a number of theoretical models that can be used to examine the interaction of AI, management, and organizations. For example, AI represents an advanced, high-level type of IS, and therefore one or more existing IS implementation models may provide useful insights for analyzing AI implementations. To date, there is no central set of constructs, as existing models focus on a limited set of variables. A review of several potential models from several disciplines is presented below.

Socio-Technical

Based on a literature review, Sharma et al. (1991) proposed a socio-technical model that seeks to answer some of the important questions behind ES deployment, such as: What are the procedures that facilitate successful implementation? Under what conditions are positive impacts realized? What are some of the underlying causal relationships? This model simultaneously addresses the technical dimension, including task scope, computer platform, and knowledge engineering process, and the social dimension, including user interaction, manager support, and organizational fit.

The model suggests that the quality of an ES is a function of the nature of the task, the technology used, people support, organizational parameters (such as culture, structure, and external environment), and the related interactions among these components.

Management Strategy and Structure.

The management literature offers a number of perspectives on the determinants of organizational structure. Chandler (1962) is responsible for the classic work on organizational strategy and structure and has strongly influenced current work in this field.

According to Chandler, companies New structures are created to meet the administrative needs that arise from the expansion of a company's activities into new areas, functions, or product lines.

A new strategy requires a new structure or redesign to maintain or improve the efficiency of the organization. A number of companies, including Texas Instruments, Arthur Andersen, and Fujitsu, are using AI strategically either to increase the efficiency of their operations or to sell AI systems as new products. (Feigenbaum et al., 1988).

In these types of firms, the theory of strategy-structure relations provides a basis for analyzing the interaction of AI, management, and organizations. For example, firms that aggressively pursue AI may need structures that promote environmental scanning, flexibility, and lateral communication.

Organizational Innovation

If AI deployment is viewed as a technical innovation, organizational innovation models are particularly well suited to studying the interaction of AI, management, and organization. According to Kwon and Zmood (1987), organizational innovation can be viewed as a three-stage process: initiation, adoption, and implementation. Initiation arises from pressure for change, adoption involves the provision of resources, and implementation refers to development, installation, and maintenance activities.

Others have expanded the implementation stage to include acceptance, use, performance, satisfaction, and integration. (For example, Rogers, 1983; (Schultz et al., 1984). These models are valuable because the phases address specific technical, motivational, and political issues and encompass a number of related constructs.

Task-Based

Since the focus of implemented AI is on automating or supporting specific tasks, models that focus on the task-based management level, rather than the broader organizational context, are relevant for providing insights into the adoption and implementation of AI.

This can allow for generalizations to specific task areas and perhaps even job groups, but since these models are below the organizational level, they are not suitable for analyzing entire organizations. Peru (1967) is a well-known example of this approach.

He argued that tasks and perhaps even entire occupations (e.g., accountants, engineers) or parts of common job tasks (e.g., tax accountants) can be meaningfully differentiated based on how information and knowledge are used to perform the tasks and to address the exceptional nature of such tasks. O'Keefe et al. (1993) have used these ideas in their analysis of ES implemented in accounting and show the differences between tax and audit ES that are expected from the model.

Implementation of Information Systems

There is considerable research examining the factors associated with the adoption, development and successful implementation of IS. Lucas et al. (1990) proposed a model of IS implementation that consists of manager and user models.

The manager model includes top management support, management belief in the system concept, and manager-researcher participation, while the user model includes user knowledge of the system's purpose, user personal stakes, and user job characteristics. This model also links the factors together and is attractive to AI and ES researchers for three reasons.

First, it integrates previous findings on IS implementation research. Second, it takes a view based on the relationships between factors rather than simply the presence or absence of such factors. Third, the model is two-stage, with one stage representing management initiation and support, and the other representing user acceptance and use.

Information Systems Implementation and Organizational Innovation

Kwon and Zmod (1987) combine the stages of the organizational innovation process (initiation, adoption, and implementation) with IS implementation factors such as individual, structural, task, and environmental factors to create a model that provides a more complete view of what is.

By themselves, it is found in any of the models of organizational innovation or IS implementation. By integrating these two streams of research, the model provides a basis for examining the multiple factors associated with implementation, innovation, and diffusion. This model is particularly appropriate when considering AI as both an IS implementation and a technological innovation.

Directions for Research

Using a simple framework that focuses on AI and its separate interaction with management and organizations, we discuss the interaction of AI, management, and organizations and provide a number of examples to illustrate the nature of these interactions. In summary, the dominant methodological approaches to studying AI in organizations, namely case studies and empirical We have described. Finally, we have presented several theoretical approaches in the IS implementation, organizational innovation, and management literature that are suitable for future research.

We suggest three directions for future research. First, existing theoretical models in the field of AI should be reexamined and augmented with propositions emerging from existing case studies to create a more comprehensive model of AI innovation and implementation.

The work of Sharma et al. (1991) is a step in this direction. Second, specific critical factors should be examined in case studies and across multiple organizations to better understand the impact of the presence (or absence) of factors related to development, implementation, and adoption.

This research should include factors that have been shown to be important in the IS literature (e.g., senior management support) and those that are likely to be new to AI adoption (e.g., “experts”). Third, case and empirical studies to date have focused on systems. Studies that focus on an entire organization (or a significant portion of an organization) provide insight into how AI is adopted and deployed throughout an organization.

For example, a case history of the life cycle of an internal AI group may provide significant insight into these issues. Regardless of the research questions addressed and the methodology used, the proliferation of AI technology provides multiple systems to study. It seems a good time to advance research on The topic will be artificial intelligence, management, and organizations.

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