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Trends in expert system development: A longitudinal content analysis of over thirty years of expert system case studies

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ABSTRACT

Research in Expert Systems (ES) has been one of the longest-running, and most successful areas of on-going research within the AI field. Since the 1980s, many case studies of ES applications have been published covering a wide range of functional areas and problem domains. These case studies contain an enormous amount of information about how ESs have been developed and how the tools, concepts, and applications have evolved since their inception. This research has painstakingly collected and analysed the content of 311 ES case studies dating from 1984 through 2016. A detailed content analysis was performed on this corpus in order to capture as many details as possible from each case. Further value was added to the study by using an impact scale to try and gauge the impact or "success" of the resulting application. With such a large sample size, the results are helpful in identifying how ES research has evolved and areas for further research.

1. Introduction

Expert Systems (ES) as a field of study within AI has now been around for several decades. Since its inception in the 70s and its rise to popularity in the 80s and 90s, many case studies have been published containing a wealth of knowledge about what worked and what did not work for that particular application. These case studies have been published in a wide variety of journals and books and reflect an extensive range of industries and different problem domains. This research project was begun over twenty years ago as an effort to try and capture the vast knowledge contained in this large corpus of case studies in order to try and provide better guidance to future ES developers.

Adelman (1989) was one of the first researchers in this area to design experiments to objectively compare the effectiveness of different KA techniques. In his 1989 paper, he identified the five determinants of the quality of the resulting knowledge base. These are:

Adelman's research was used as a general framework for the current study. Expert system case studies were examined in detail for any information regarding the problem domains, KA techniques, knowledge representation schemes, domain experts, KEs, and anything else that might possibly be of interest. They were analysed using a technique called "content analysis". Given the large number of detailed case studies it was hoped that this exploratory study might reveal past and current trends in expert system research. Further value was added to this study by applying a measure of system success related to the "impact" of the application as described in the case study (Wagner, Chung, & Najdawi, 2003). This can help us begin to make some normative suggestions about what works and what does not in the ES development process.

1.1. Methodology

This research applies a qualitative research method called "content analysis" to the large body of expert system cases reported in the literature. The cases were selected on the basis of whether they included enough useful details about the actual expert system development process. Some cases had very little to say about the five determinants listed in Table 1 and spent the whole paper describing the actual domain knowledge used in the applications. On the other extreme, some cases were very detailed and included lots of information about the system development process. As the work progressed, it became clear that the concept of the "classic" expert system with a single human domain expert working with a knowledge engineer had evolved into more of a hybrid knowledge-based system with multiple knowledge sources used to develop the system. This trend becomes more apparent when viewed longitudinally over the period of this study from 1984 to 2016.

Liao (2005) previously published a review of ES research which used a key word search methodology to identify 98 ES papers that focused on "expert system methodologies" that were published between 1994 and 2005. A wide search for expert system case stud-

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Table 1
Determinants of knowledge base quality (Adelman, 1989).

(1) Domain experts (DE)
(2) Knowledge engineers (KE)
(3) Knowledge representation (KR) schemas
(4) Knowledge acquisition (KA) techniques
(5) Problem domains

Table 2
Total case studies by functional areas.

• Accounting – 33
• Finance – 66
• HR – 12
• Management – 47
• Marketing – 13
• Operations – 103
• Production – 37

ies was used initially and this led to the discovery of some very useful case studies in such journals as *Managerial Finance, European Journal of Operations Research,* and *Computers and Biomedical Research.* Many case studies were published in other industry specific journals in the fields of Medicine, Finance, and Accounting besides ES-specific journals. Some excellent cases were found in several edited books. These included *Innovative Applications of Artificial Intelligence* (from the annual IAAI Conference), and *Operational Expert Systems in Europe* (also for Far East, Mexico, USA, and Canada). They contained some very detailed and high quality case studies of operational expert systems. There was so much detail in fact, that the content analysis database had to be revised several times in order to accommodate interesting details such as multiple KA phases, multiple knowledge representation schemas, number of rules, and actual development cost data. This further required that the previously analyzed cases had to be reviewed again. Once the widely scattered case studies were studied, then key journals such as *Expert Systems with Applications, Expert Systems*, and *IEEE Expert* were systematically surveyed for further case studies.

This study is also unique in that it is longitudinal in nature; covering a total of thirty-three years of case studies from 1984 to 2016. Based on the publication date, the corpus of 311 case studies was further broken down into three year increments for the purpose of this present study. Because the study uses the publication date as the "date" of each individual case study, viewing them in three year increments helps to remove some of the lumpiness of the data due to a large edited book of case studies coming out in a certain year.

1.2. Content analysis for case studies

Content analysis is a robust research tool combining both qualitative and quantitative aspects that has been actively used in many fields for more than fifty years. It is used to determine the presence of certain words or concepts within individual or groups of texts. Using content analysis, researchers quantify and analyze the presence and relationships of these key words and/or concepts in order to make inferences about the issues being studied. This methodology has been applied successfully to the study of texts such as essays, books, discussions, newspapers, quarterly reports and virtually every type of printed communication (Krippendorff, 2004). The output of such research is useful in important concepts and when used in a longitudinal analysis, can be helpful in identifying trends.

In order to conduct a content analysis on any text, the text must be coded, or broken down, into manageable categories in differing levels of granularity. This could include – word, word sense, phrase, sentence, or concept. Within content analysis there are a number of quantitative and qualitative variations in the methodology. However, content analysis has most often been applied for conceptual analysis. In conceptual analysis, a concept is chosen for examination, and the analysis involves quantifying and tallying its presence (Krippendorff, 2004).

In this particular study, the focus was on looking at the occurrence of selected terms and concepts within the entire corpus of expert system case studies. These terms and concepts may be implicit as well as explicit. So it is necessary to do a close reading of each case study in order to code more interesting details about concepts such as the problem domains used or deriving an estimate of the "impact" of the expert system. By carefully delineating the notion of the key determinants of interest and also the impact scale in advance, this helps to limit the subjectivity of the coding process.

This study manually analyzed the entire corpus of expert system case studies and coded every possible detail into a database. This included important items such as the KA technique used, the problem domain addressed, the industry, the knowledge representation used, characteristics of the domain expert, and the various phases of knowledge acquisition. The coding scheme for the KA techniques used was derived from the proposed taxonomy of KA techniques presented by Boose (1989). More granularity for coding the problem domains was added by using the problem domain taxonomy proposed by Clancy (1986) as described in Section 2.3. Further value was added to this study by measuring the "impact" of the expert system (see Section 3) and also coding this into the content analysis for each case. This measure of the ES impact was developed and used in an earlier study which examined a much more limited set of over 100 ES case studies derived from the P/OM functional area (Wagner et al., 2003).

2. Dimensions of current study

A content analysis of expert system case studies can be useful to confirm some trends and explore new ones. For example, it is well-known that there has been a marked decline of the "classic" expert system in favor of hybrid, knowledge-based systems. These typically employ a variety of AI techniques including neural networks, fuzzy logic along with some rules. It is also common knowledge that Lisp machines and Prolog are not in regular usage any more. However good information about the trends in problems domains, knowledge acquisition tools and techniques and how knowledge representation schemes are being used is certainly less common. These dimensions are explored in more detail in the following sections.

2.1. Expert systems by functional area

From the organizational viewpoint, most of the ES applications were from business- oriented organizations. The totals for the functional areas where these applications were implemented are broken down in Table 2.

When viewed the 33 years encompassed by this study, some further trends can be seen. It seems that after a brief period in the late 80s and early 90s, hardly any applications in the area of HR, Marketing or Accounting and Finance have been attempted. This may represent a general decline in range of ES systems being developed. Though there was a slight uptick in the number of published case studies in the late 2000s. Fig. 1 shows the overall distribution of expert system applications over the 33 year time horizon of the study. It should be kept in mind that the functional area assigned to an application represents the department in which the application was implemented and not the industry in which it is

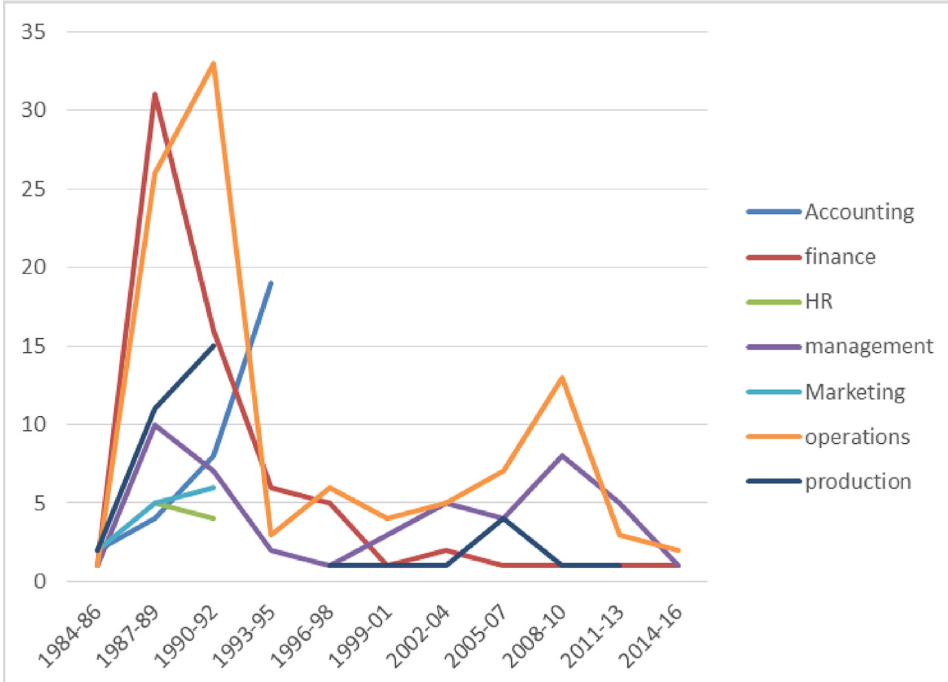

Fig. 1. Expert system applications by functional area over time.

used. So it is possible that an HR expert system for personnel evaluation could have been developed for a company in the aeronautics industry.

Several trends are clear from this chart. First, it shows that there was a major spike of interest in expert systems in the late 80s and early 90s. These systems were also originating mainly in Operations (including Scheduling applications), Finance, and Management. There was some interest in applications for Production (manufacturing) and Accounting. And as might be expected, HR and Marketing were the last. After this spike in interest however, applications were generally limited to operations and general management. This may be due to the fact that the majority of interest in expert systems has come from areas with well-structured problems such as operations or finance that can be more easily programmed as expert system applications.

2.2. Expert systems by industry

When viewed by specific industries, it is amazing to see how many different industries have employed this technology. The distribution shows what a wide-ranging AI application ESs have been. The total distribution among different industries is shown in Table 3.

The most popular industries for expert system applications were accounting and financial services, manufacturing and medicine. These are industries that are quick to explore and adopt new technologies such as expert systems. They also typically devote more resources to information technology since they have a greater potential payback. Not surprisingly, the industry laggards were publishing, real estate, and legal services. It was a little surprising that the transportation industry was also on the low end of the industry applications. This longitudinal analysis of applications by industry also shows that in the last ten years, the medical industry has taken over as the most popular in industry for expert systems by far. And interest from the other industries has dropped substantially.

Table 3
Expert systems applications by industry.

Accounting services	34
Aerospace	13
Agriculture	6
Automotive	13
Banking	30
Chemical	5
Construction and mining	7
Education	14
Financial services	28
Government	10
Healthcare	4
Info tech	14
Insurance	12
Legal services	2
Logistics	8
Manufacturing	31
Medical	24
Military	14
Oil and gas	11
Publishing	1
Real estate	1
Retail	6
Scientific research	3
Telecommunications	11
Transportation	2
Utilities	7
Total	**311**

2.3. Problem domain trends

The concept of a “problem domain” describes the general focus or issue of the particular application. Because expert systems have to have a very well-defined problem domain in order to function, this is an especially important concept and one of the most important determinants of ES quality (Adelman, 1989). Clancy (1986) supplied a much more detailed taxonomy for describing problem domains based upon how the knowledge is applied to the problems. Generally speaking, “analysis” problems involve breaking the problem down into sub-problems. These are typically more

Table 4
Taxonomy of problem domains (Clancy, 1986).

Analysis problems
■ Classification – categorizing based on observables. ■ Debugging – prescribing remedies for malfunctions. ■ Diagnosis – inferring system malfunctions from observables. ■ Interpretation – inferring situation descriptions from sensor data.
Synthesis problems
■ Configuration – configuring collections of objects under constraints in relatively small search spaces. ■ Design – configuring collections of objects under constraints in relatively large search spaces. ■ Planning – designing actions. ■ Scheduling – planning with strong time and/or space constraints.
Problems combining analysis and synthesis
■ Command and control – ordering and governing overall system control. ■ Instruction – diagnosing, debugging, and repairing student behavior. ■ Monitoring – comparing observations to expected outcomes. ■ Prediction – inferring likely consequences of given situations. ■ Repair – executing plans to administer prescribed remedies.

Table 5
Expert system totals by problem domain.

Classification	26
Debugging	16
Diagnosis	73
Interpretation	27
Control	10
Instruction	10
Monitoring	33
Prediction	15
Correction/repair	7
Configuration	14
Design	28
Planning	41
Scheduling	11
Grand total	**311**

easily structured problems. On the other end of the taxonomy are “synthesis” type problems. These involve putting together resources in different combinations and these are generally more unstructured type of problems. Other problems such as monitoring or prediction, combine aspects of both analytic and synthetic problem domains. This is reproduced in Table 4 below:

There has been some earlier research conducted in this area that focused on the *problem domain* as a determinant of expert system quality (Wagner & Zubey, 2005; Wagner et al., 2003; Wagner, Chung, & Najdawi, 2001; Wagner, Otto, & Chung, 2002). Further credence regarding the relative importance of the problem domain comes from reports of expert system developers (McGraw & Harbison-Briggs, 1989; Tuthill, 1990) that indicate that certain types of problems are more difficult to develop applications for, but typically yield higher impact systems. This assertion was basically validated in the Wagner et al. paper from 2003 which performed a content analysis of over 100 expert system case studies in the P/OM area. This study determined that even though they were more difficult to elicit knowledge about, *synthetic problems* yielded expert systems that had a greater average impact than those developed for *analytic types of problems*. Table 5 shows the overall distributions of these different problem domains in the current study.

Given the popularity of such applications as Mycin from the early days of expert systems research, it is not surprising that “diagnostic” applications continue to dominate the field. Fig. 2 shows the trends for different problem domains in the last thirty-three years.

While Fig. 2 does indicate that diagnostic applications have always been popular, it also shows that there has been substantial interest in designing expert systems for planning, monitoring, and interpretation type problems. In particular, there was a certain resurgence in monitoring applications in the last ten years. This may have been due to the more recent emphasis on real-time applications involving sensor data.

2.4. Trends in knowledge acquisition techniques

In the early years, it was often the case that the domain expert and the knowledge engineer were one and the same. So at that time there was little discussion about the knowledge acquisition (KA) “bottleneck”. After key research identified this issue (Boose, 1989; Clancy, 1986; Cullen & Bryman, 1988; Fellers, 1987; Hoffman, 1987; Kim & Courtney, 1988) there was much more of a focus on using the appropriate technique for the project. Most of the experimental research conducted on the KA problem has focused on the specific KA techniques that were used in the development process (Boose, 1989; Burton et al., 1990; Dhaliwal & Benbasat, 1990; Raj, Holsapple, & Wagner, 2008; Wagner, 2006). Empirical research in the field of expert systems revealed that certain KA techniques are significantly more efficient than others in different problem domains and KA scenarios (see Wagner et al., 2001 for summary).

In the past, researchers either borrowed interviewing techniques from the field of psychology, or wrote programs that helped automate and structure the interview process. These KA techniques are generally categorized as either being *manual* or *computer-based* techniques (Dhaliwal & Benbasat, 1990). While working on this project some of the categories were updated to include the possibility of computer learning techniques such as ANNs, Bayes Networks and also case-based reasoning being integrated into the project. Computer modelling was expanded to include a variety of computer generated models such as repertory grids, multidimensional scaling and semantic networks. On the “manual” side, the idea of the “structured interview” category includes how a KE can use tools such as surveys, focused questions, knowledge maps and even the prototype systems themselves to help structure the interview. Since they were popular at one point, some other specific KA techniques were included such as protocol analysis (verbal, video, and textual) along with KE observation and KE tutorials.

After analysing this large corpus of case studies, it is clear that the system developers had widely varying views of the knowledge acquisition (KA) process. A large number of them (80) did not bother to mention the process, while many of them just made a cursory mention of “interviewing” the domain expert. When this was the case, it was entered in as an “unstructured” interview. In the late 80s and early 90s there seemed to be a bigger emphasis on tracking the KA techniques used and this is reflected in

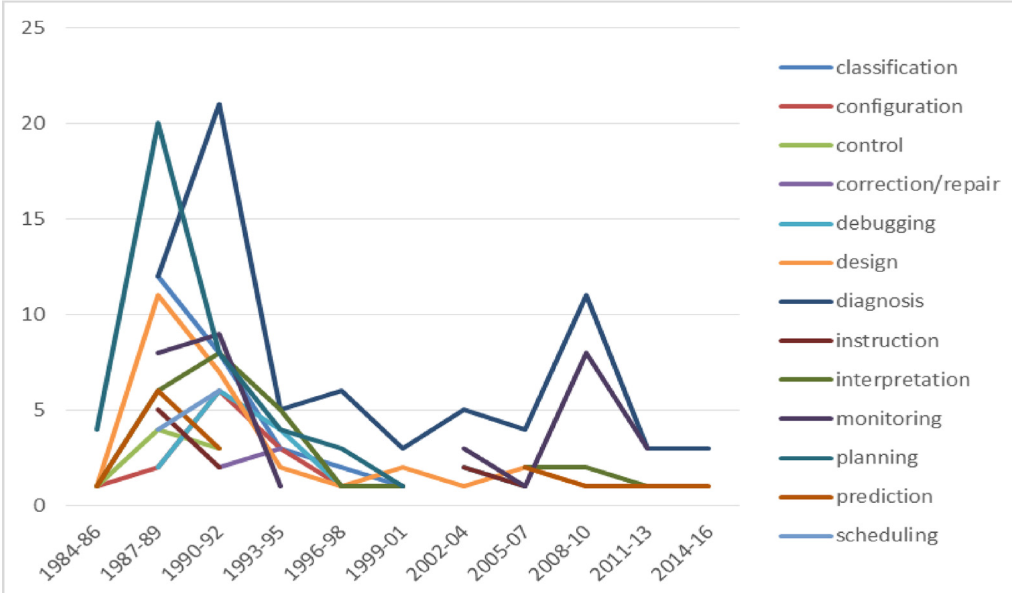

Fig. 2. Expert systems problem domains over time.

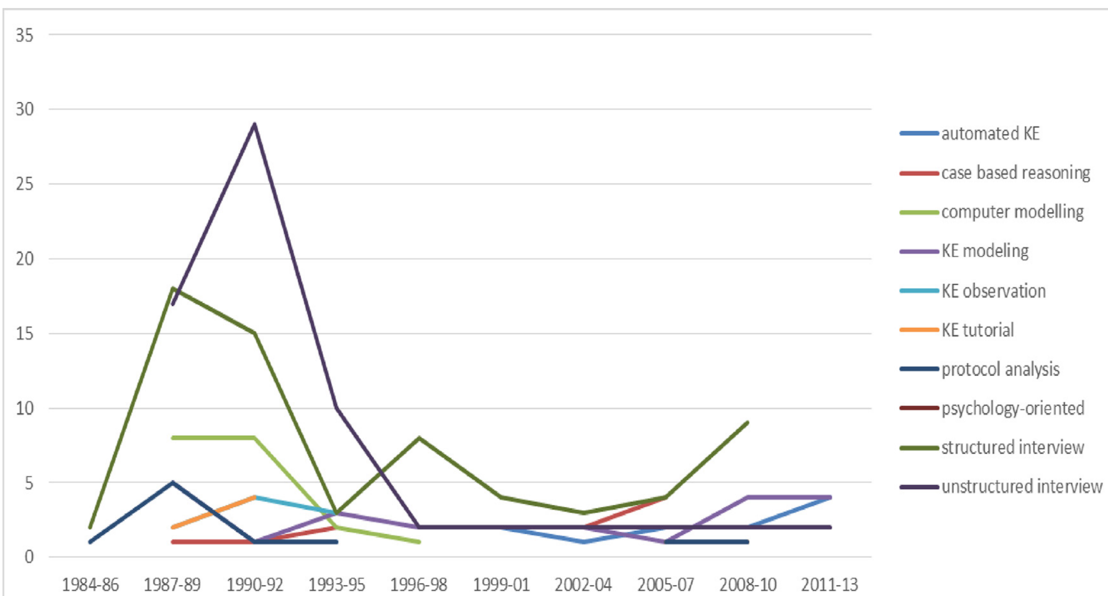

Fig. 3. Expert system KA techniques over time.

Fig. 3. With respect to the category called "structured interview" in the manual category, this would include a wide variety of ways that the KE could use to give the interview some kind of structure, such as surveys, lists, and the use of an early prototype system for feedback. KE modelling refers to KA techniques that involved more specific tools such as dependency diagrams, knowledge maps, cognitive maps, decision trees, etc. Not surprisingly, unstructured interviews were one of the most common techniques used as opposed to psychology-oriented techniques and protocol analysis even though these have been shown by various experiments to be more effective (Wagner et al., 2001). Around 1996 however, structured interviewing seems to have overtaken unstructured in general usage and continued to be more popular until about 2009. After this, no structured interview case examples were published along with other missing KA techniques such as CBR, computer modelling, KE observation, KE tutorial, computer modelling, and psychology-oriented techniques. A recent uptick in automated KE may be due to increased interest in neural networks and semantic ontologies for KA (see Table 6).

2.5. Knowledge representation trends

One of the more difficult determinants to accurately track is that of the particular knowledge representation (KR) schema used. While certain KA techniques and expert system platforms may lend themselves to a particular KR schema, in practice there may be many different intermediate KRs used. These could include semantic nets, ontologies, decision trees, cases, neural nets, etc. To simplify this research, a target or primary KR schema was identified and additional intermediate KRs were tracked separately when they were included in the case study. Table 7 shows the totals for all of these primary KR schemata.

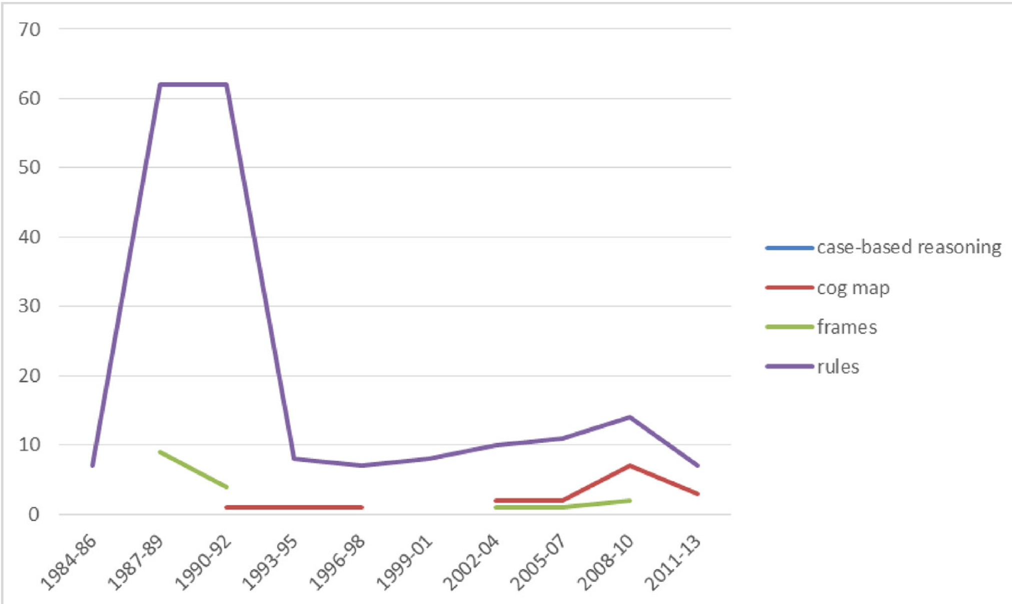

Fig. 4. Expert systems by KR schema over time.

Table 6
KA techniques for ES development (adapted from Dhaliwal & Benbasat, 1990).

Computer-based approaches	
Automated learning/KE	13
Case-based reasoning	10
Computer modelling	21
Manual approaches	
Unstructured interview	68
Structured interview	66
KE modelling (knowledge maps, etc.)	22
KE observation	10
KE tutorial	9
Protocol analysis	10
Psychology-oriented (card sorting, etc.)	2
Indeterminate	80

Table 7
Knowledge representation schema totals.

Case-based	1
Cognitive map	17
Frames	18
Indeterminate	79
Rules	196
Total	**311**

A good number of case studies did not mention the actual KR used and some only mentioned one KR schema. Others have mentioned multiple intermediate KRs. Clearly, rules still tend to be the dominant KR used. This may also reflect the bias of this study towards ES case studies which embody the "classic" ES involving one or more human experts. Fig. 4 shows how the use of KRs has changed over the last 33 years. A wide variety of intermediate KRs are often used too, but these are often poorly documented.

3. Impact scale for measuring expert system success

The notion of measuring the "impact" of any information system application is important because it allows researchers to suggest normative conclusions from the data. An impact assessment of expert systems, or knowledge-based systems (KBS) in general, should be integral to an organization's overall implementation decision. Merely considering the technical feasibility and cost-effectiveness cannot provide a complete understanding of impact and success from the organizational perspective. Changes that may come about due to the introduction of the KBS or expert system must also be considered to fully ascertain the organizational impact of the systems.

Past research in the evaluation of expert systems has typically focussed on the technical system parameters, usually ignoring other factors. A precursor to this current study proposed the creation of an "impact scale" to better assess the overall impact of the ES application beyond just the technical success (Wagner et al., 2003). This scale is useful for coming to some normative conclusions about the overall ES development strategies and is important for comparing alternatives given the large corpus of case studies that have been accumulated over time.

In the present study, the ES application "impact" was represented with an ordinal scale from 1 to 7; where at the low end you might find prototypes that may or may not have been field tested, while at the high end, would be systems that resulted in cost savings and structural change to the organization. In the middle you would have systems that were implemented and were tested and validated but had no reported cost savings or changes in the organization. Beyond this, systems that were implemented fully may have resulted in varying degrees of cost savings, increased satisfaction, and even organizational change. Though it may still be crude, this metric goes beyond simply counting the number of rules in the knowledge base or evaluating the accuracy of the rules and provides a more comprehensive tool for case analysis. This approach to measuring impact is more comprehensive than previous ones because it is flexible enough to combine all the elements that constitute what might be thought of as technical, economic and organizational success.

3.1. Impact of functional area expert systems

At the highest level, it is interesting to consider general functional areas and the relative impact of expert systems developed for them. Fig. 5 shows the relative impact of these systems based on the average of the impact ratings assigned to each of them.

Fig. 5. Average impact of ES by functional area.

The two areas with the fewest reported applications (HR and Marketing) both have the highest average impact factor. Production and Finance have the highest number of applications developed for them and have relatively high impact too. The lowest impact is in the area of Accounting. This may say something about the organizational readiness or the general usage and acceptance of AI within these different functional areas, since there is a long history and experience of using ES technologies in Finance and Production.

3.2. Impact and industry

No studies to date have actually looked at the specific industry to see which ones have the most impactful systems. One study (Liao, 2005) did list the specific applications for 98 cases from a ten year period, based upon the methodology they used (rule-based, neural net based, etc.). From the analysis provided here, publishing had the highest average impact system, though this should be discounted since there was only one example system in the publishing area; making this a possible outlier. Some of the next tier industries with respect to the impact of the ES applications include aerospace, chemical industry, logistics, and telecommunications. Some of the lowest impact systems were developed in the areas of agriculture, medicine, real estate, scientific research, and transportation. It may be that some of these industries did not have the infrastructure or managerial expertise to successfully implement these systems throughout the organization (see Fig. 6).

3.3. Impact and problem domain

This is possibly the most interesting area for examining the impact of the expert system application. This is because companies may want to actively pursue developing applications in these problem domains in the future. Fig. 7 shows the average impact calculated for each of the different problem domains. The chart is color-coded to indicate the general category of problem domains as described earlier in Table 4. The highest impact problem domains are all in the category of "synthetic" problems. This supports the observation by KEs and also an earlier study of problem domains, that synthetic type problems are harder to develop applications for, but have a higher impact (Tuthill, 1990; Wagner et al., 2003). The corollary to this is that analytic problem domains are generally easier because they are more structured, but have less of an impact on the organization.

3.4. Impact and knowledge acquisition techniques

If we examine the average impact of the expert systems that have been developed with different KA techniques, the picture is less clear. In the past, it was thought that unstructured interviews were inefficient and yielded less knowledge and therefore, poorer quality expert systems (McGraw-Harbison Briggs, 1989; Tuthill, 1990). According to this more comprehensive study, structured and unstructured interviews yielded the highest impact systems. KE tutorials were actually the highest but had a very limited sample size (9). There were a large number of published cases of systems that did not go beyond the basic validation of the application rules and so this pulled down the overall averages. Interestingly, computer modelling was the highest for the computer based KA techniques and was higher than KE modelling (see Fig. 8).

3.5. Impact and knowledge representation schema

Measuring the impact of the different knowledge representation (KR) schemas may be even more problematic. Many times, the actual KR used was impossible to determine and at times, the authors may have focused solely on an intermediate KR in their write-up of the application. Still, it is interesting to examine the impact of different KRs as it is shown in Fig. 9.

It has been noted in the past that frames are especially good at representing "deep" knowledge of the domain expert (McGraw & Harbison-Briggs, 1989). It is impossible to verify this with this study. However, even with the large number of rule-based systems studied here, it seems that rules produce applications with the highest impact. Frames are second and cognitive maps are third. Very few reported applications used decision trees, so this category may not be meaningful in this study. More recent case studies focus on the creation of ontologies which might fall under the general category of cognitive maps. However, these cases were not included simply because they did not have enough detail about the expert system development process. It is also clear that what

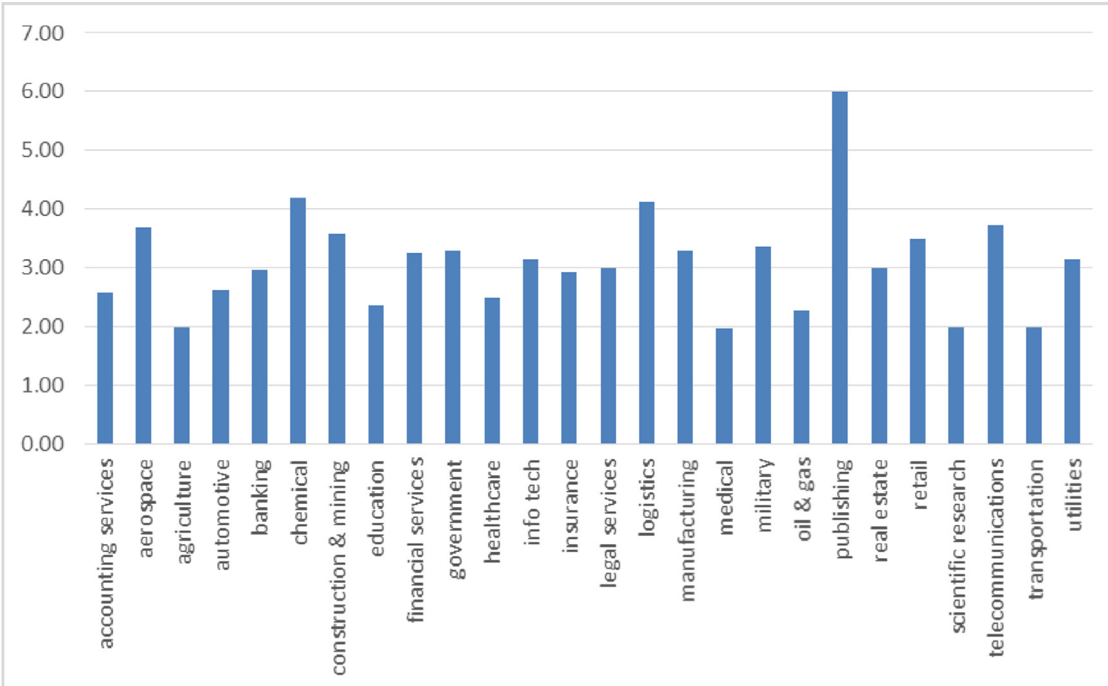

Fig. 6. Average impact of ES by industry.

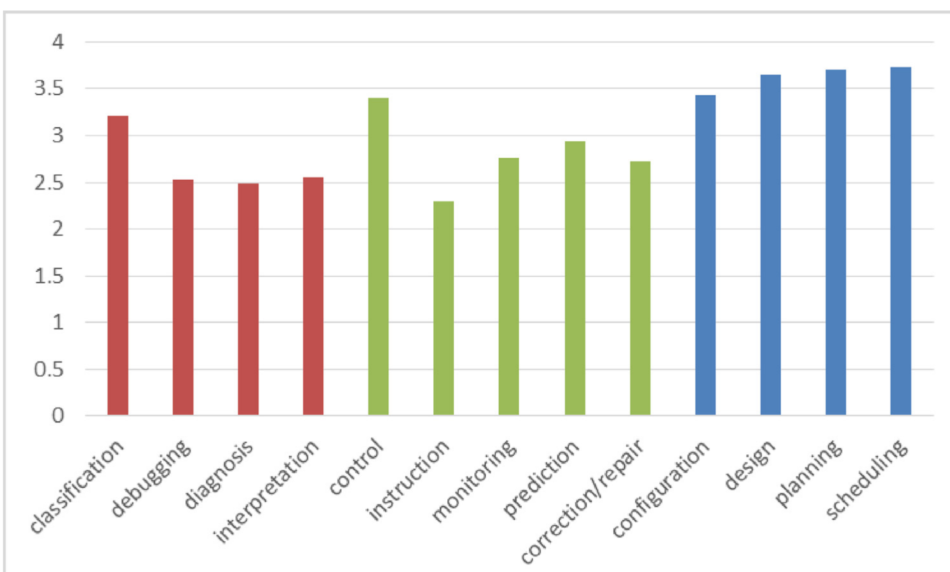

Fig. 7. Average impact of ES by problem domain.

drives the choice of KR is often the particular ES development tool used and/or the KA technique used. Although in many cases, multiple intermediated KRs (tables, scripts, trees, fishbone diagrams, etc.) may be involved before the final KR schema is completed.

4. Overall analysis and future directions

This research describes an ongoing project that spans thirty-five years of expert system case studies. These case studies are the source of many good observations from actual designers and practitioners. A content analysis of 311 case studies was performed using Adelman's (1989) framework of the key five determinants of expert system quality. The key determinants tracked in this study include the problem domain, KA technique uses, and the KR schema used. The results were further characterized by using Clancy's taxonomy of problem domains and Dhaliwal and Benbasat's listing of KA techniques.

This research confirmed some known trends and identified some new ones. It is clear that research in this field has moved away from the "classic" expert system with one or more human experts, to a hybrid model of knowledge-based systems that incorporate a variety of AI tools and techniques. There is also less research today focusing on the variety of KA techniques used to develop the system. Diagnostic expert systems continue to be one of the most popular types of applications. This research also verified the earlier study (Wagner et al., 2003), which found that synthetic type problems had a higher impact in general. From the longitudinal analysis, earlier systems seemed to report a greater impact

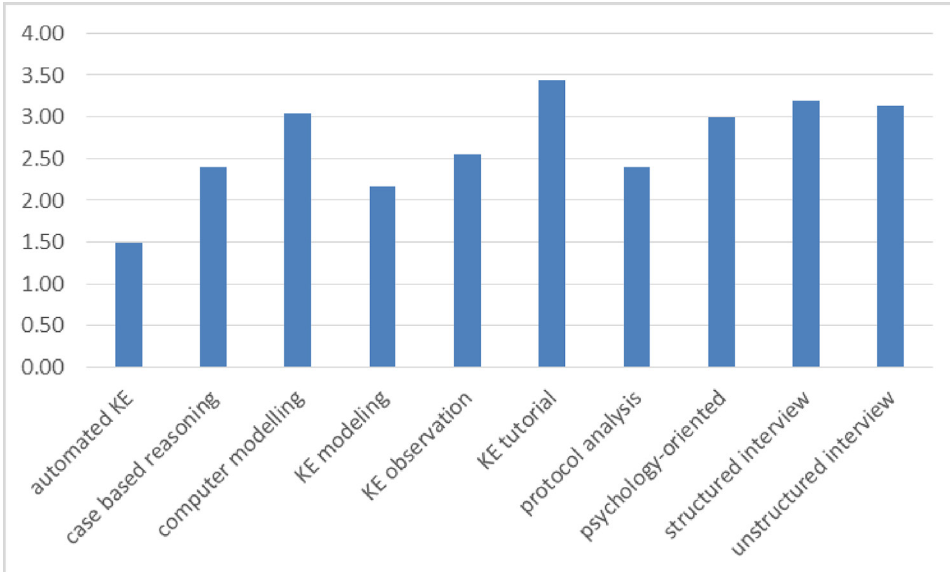

Fig. 8. Average impact of ES by KA technique.

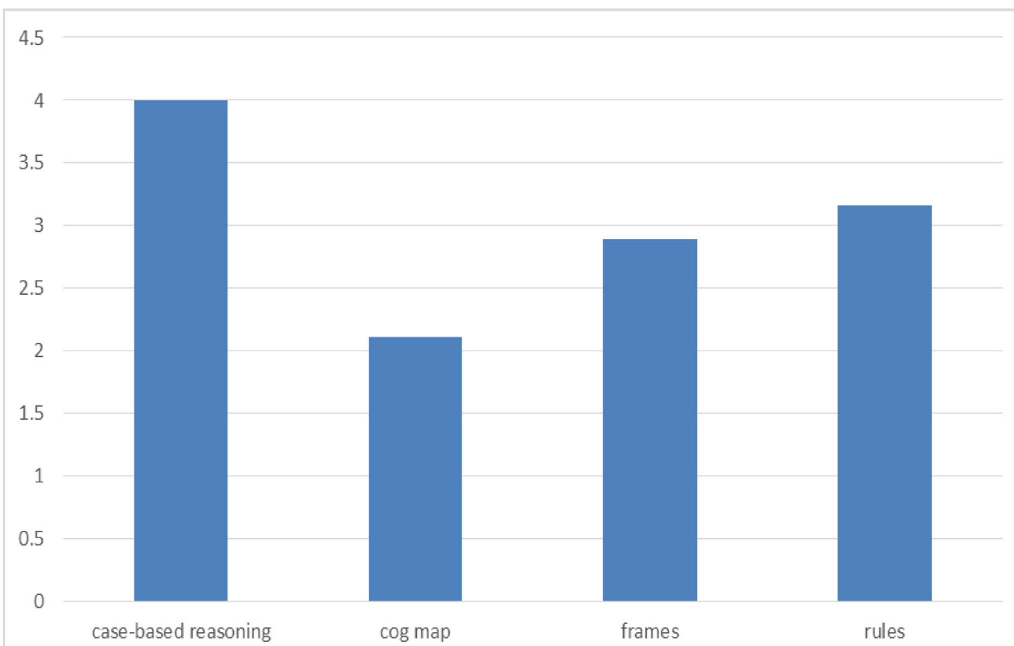

Fig. 9. Average impact of ES by KR schema.

of their applications that the more recent ones. This may be due to the fact that earlier developers were able to identify the "low-hanging fruit" which had bigger potential impact on the organizations. Fig. 10 below seems to show that this is the case.

This trend in reporting lower impact ES cases may also be the result of changes in the publication process, with fewer case studies on mature ESs and more emphasis on reporting about prototype applications.

With respect to KA techniques that have been used, unstructured interviews were more common early on and structured interviews continue to be more popular recently. Both of these techniques had higher overall average impacts along with computer modelling from the computer-based KA side. Some of the more exotic KA techniques such as card-sorting, brainstorming and Delphi method had very few examples in the corpus, so it was difficult to gauge their effectiveness. Protocol analysis, which has been shown to be very effective in KA experiments, has fallen out of favor in recent years. One unforeseen benefit of developing the ES application was that many of them ended up being used for training non-experts within the organization.

Little research has examined the actual effectiveness of the KR schemas used. This is complicated further by those applications that report using multiple intermediate KR schemas before the final KR. A lot of the choice in KR used seems to be driven by the ES platform that the developers have chosen and not by any particular "fit" of that particular KR with the knowledge being elicited. The majority of applications continue to be focused on using rules for the KR, although there is some movement towards a variety of cognitive maps. Rule-based and frame-based applications have the

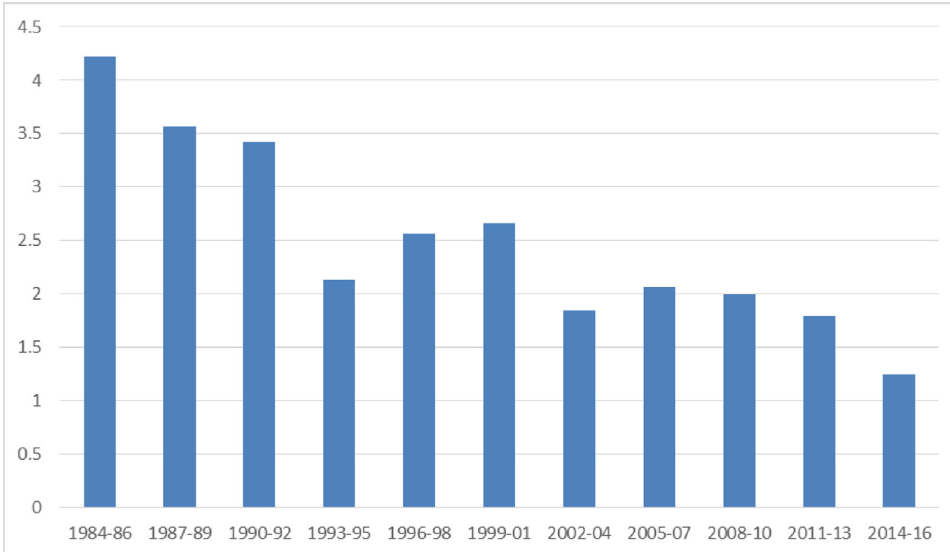

Fig. 10. Average impact of ESs over time.

highest impact, though the use of frames for the KR has declined significantly.

This research has shown how expert systems applications have evolved and can also provide some guidance for future ES developers. Given the large number of case studies that have been analysed as a part of this research, it seems clear that some problems have a higher potential impact than others. The same may hold true for specific functional areas, KA techniques, industries and KR schemas. Future research can also examine the use of multi-phase KA, multiple experts, ontologies, and the wide variety of intermediate KR schemas that have been used. It would also be interesting to examine certain powerful combinations of problem domains, KA techniques and KR schemas to see if there are natural combinations that yield better applications.

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