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Knowledge Management in the Construction Industry: Integration between Research and Practice

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Abstract*— The construction industry is characterized by the production of massive number of documents in different formats. Successful completion of projects is highly dependent on efficient communication of essential information conveyed by these documents. Furthermore, the majority of decision making processes involve assimilating previously gained experiences from similar projects with newly introduced information. Being highly reliant on human intervention, such processes are time demanding and prone to error. Consequently, effective knowledge management systems are essential for guaranteeing thriving future of this industry. A number of researchers have created automated and semi-automated tools in an attempt to facilitate knowledge management. Although these endeavors have achieved progress, their integration into the profession has not yet reached its full potential. The purpose of this paper is to provide an overview of these researches, and identify parameters hindering their integration into the construction practice. The adopted research methodology developed a comprehensive corpus of peer-reviewed publications; identified the capabilities of the developed tools and systems; and highlighted the main factors delaying their incorporation into the practice. The outcomes of the current research task recognized three main factors contributing to the resistance of integration, namely access to large databases, interoperability, and the need of a cultural change.

***Index Terms*—Artificial Intelligence (AI), Construction Management (CM), Information Modeling, Knowledge Management (KM).**

I. INTRODUCTION

The construction industry is characterized by being ever evolving, dynamic, and rapidly integrating new technologies. These unique characteristics mandate specific constraints including but not limited to extensive coordination, far reaching collaboration, overcoming geographic boundaries to involve professionals with different experiences, implementation of various decision making techniques, and the generation of documents in different forms. Some documents are produced in a structured format like AutoCAD drawings, 3-D models, and schedules. However, the majority of the documents are stored in semi-structured or unstructured formats like technical specifications, general and supplementary conditions, addendums, amendments to contracts, contractual agreements, meeting minutes, daily reports, change orders, request for information (RFI), request for quotation (RFQ), claims, and litigations. Furthermore, decision making processes in construction involve problem analysis, data gathering, and judgment based on previous experiences of similar or diverse situations. As a result, any set of construction documents, including the aforementioned examples, represent the outcomes of a number of decisions throughout different phases in the life cycle of a project. These documents are the manifestations outlining the methods and processes of construction project management. These manifestations are often very complex and could lead projects to have less than successful conclusions. Effective knowledge management processes not only ensures cost, time, and quality compliance of the project, but also minimizes the likelihood of conflicts and disputes arising in these projects. At a time when nations are in need for effective management practices to address means of economy growth and unemployment problems, the Architecture, Engineering, and Construction (A/E/C) industry is in an escalating trend of efficiency loss due to the inability to effectively utilizing experiences gained from previous similar situations [1]. By definition, Knowledge Management (KM) covers a wide range of techniques and processes [2]. KM includes strategies and practices to facilitate (1) identifying; (2) creating; (3) representing; (4) distributing; and (5) enabling insight to experiences from lessons learned in previous similar situations in a manner that allows for cooperation and collaboration to achieve satisfactory completion of new projects [3]. The literature in this domain highlights that the efficiency of knowledge management tasks is hampered by the many documents that construction practitioners and professionals have to review and evaluate to perform their tasks. Many of these documents are expressed in natural language making them very difficult to be processed by computers [4]. Construction practitioners spend a large amount of time manually processing these textual documents. This time would be much better spent managing the technical aspects of the project which requires the level of knowledge and expertise of these professionals. It has been estimated that the Architecture, Engineering, and Construction (A/E/C) industry spends approximately $5 billion on conflicts, claims, and disputes [5]. It is further estimated that approximate 2% of project costs are spent on dispute resolution [6]. These large expenditures could be decreased by creating and implementing effective methodologies for exploiting, sharing, transferring, and re-using lessons learned in the

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industry to facilitate decision making. Effective management of the knowledge contained in construction documents in order to enhance project management task is therefore of great importance for the success of construction projects. In an attempt to facilitate KM in the construction industry, a number of research efforts have developed methodologies for storage, retrieval, use, and reuse of lessons learned from experience through expert systems (ES), case-based reasoning (CBR), Artificial Neural Networks (ANN), and hybrid systems. Although these efforts have achieved advancements in their respective domains, they have not reached their full potential. Thus the aim of this paper is to (1) present a comprehensive review of research literature on KM in the A\E\C domain; and (2) identify challenges to full integration of these efforts into the market. The following parts of this paper is devoted to the discussion of

- Research Methodology:
    - This section details the different stages of the research methodology.
- Knowledge Management (KM):
    - This section introduces the reader to the meaning of Knowledge Management and Knowledge Management Systems addressed under the current research.
- Research Lines:
    - This section identifies and describes research efforts in the area of KM within the different domains of the construction industry.
- Discussion:
    - This section provides the reader with knowledge about the identified challenges and potential areas for future research related to KM in the construction industry.
- Conclusion

II. RESEARCH METHODOLOGY

The adopted research methodology under the current task is composed of 3 stages as illustrated in Fig. 1. First, a comprehensive search of books and peer-reviewed publication including journals and conference proceedings was performed to develop a corpus of the existing knowledge about the domain problem. To that end, a number of search engines and databases were investigated including but not limited to the American Society of Civil Engineers (ASCE), Canadian Society of Civil Engineers (CSCE), Google Scholar, Academic Search, Cite SeerX, Association for Computing Machinery Digital Library, Science Direct, and IEEE Xplore. The search yielded a total of 96 papers and books published between 1984 and 2013. Second, content analysis was performed for inclusion and/or exclusion purposes. The analysis entails two parts. Brief analysis of the abstracts of each identified publication was done to determine its suitability for the current research task resulting in excluding 15 publications. The exclusion was due to that these publication are related to other domain problems outside of construction. Second, the content of the final 81 publications was performed to identify (1) the research methodology; (2) the final outcome of the research; (3) challenges of the research. Third, the final corpus was divided into subcategories based on identified lines of research. To that end, 3 lines of research were defined, namely Construction Law, Architectural and Civil Engineering, Construction Engineering and Management. Fig. 2 illustrates the breakdown of the final corpus per research line. The main research lines were further divided into 3 sub research streams based on domain problems, namely Expert Systems (ES), Case-Based Reasoning (CBR), Artificial Neural Networks (ANN), and Hybrid Systems (HS).

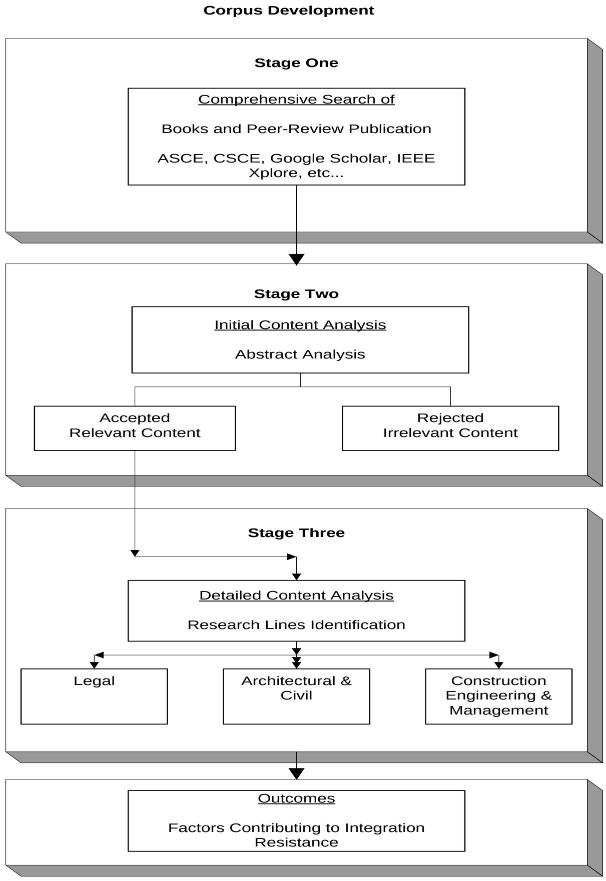

Fig. 1 Research Methodology

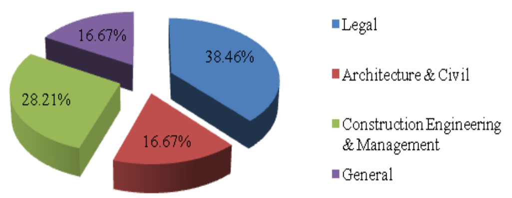

Fig. 2 Percentage Distribution of Final Corpus Per Research Line

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III. KNOWLEDGE MANAGEMENT (KM)

This section is dedicated to provide a common understanding of the definition of Knowledge Management (KM). The literature in this domain illustrates that there is no one definition that is all inclusive. KM could be defined as "efficient handling of information and resources within a commercial organization" [7]. According to [8] and [9], "Knowledge management is the process of capturing, distributing, and effectively using knowledge." A more comprehensive definition was provided in [10] stating that "Knowledge management is a discipline that promotes an integrated approach to identifying, capturing, evaluating, retrieving, and sharing all of an enterprise's information assets. These assets may include databases, documents, policies, procedures, and previously un-captured expertise and experience in individual workers." Further investigation of the topic highlights that there are common agreed upon functions in relation to KM in the construction industry, which are to facilitate (1) identifying; (2) creating; (3) representing; (4) distributing; and (5) enabling insight to experiences from lessons learned in previous similar situations in a manner that allows for cooperation and collaboration to achieve satisfactory completion of new projects [3]. Since all processes related to KM address "Knowledge", it is worth to ask "What is Knowledge?" Knowledge can be defined to encompass three types, namely Explicit, Implicit and Tacit. [9] defines them as "Explicit: information or knowledge that is set out in tangible form." "Implicit: information or knowledge that is not set out in tangible form but could be made explicit." "Tacit: information or knowledge that one would have extreme difficulty operationally setting out in tangible form." For more elaboration, a clear example of explicit knowledge in construction documents can be payment terms stated in a contract clause or the duration of project included in an agreement form. On the other hand, Implicit and Tacit knowledge can be viewed as human experiences used to define profit margins and contingency premium to bid values. They cannot be identified directly by reading a manual. Human intervention based on previous experiences of similar situations and analysis of the market as well as competition levels must be employed to make a decision about these values. As mentioned previously, the majority of decisions within the construction industry require explicit and implicit knowledge. Most of the commercially available KM tools are compatible with data in a structured form (object oriented modeling) similar to Building Information Models and scheduling packages. However, a major portion of the essential knowledge is contained in semi-structured or unstructured documents like text editor packages and spreadsheets formats. Examples of these documents include but not limited to agreements, contract conditions, change orders, meeting minutes, etc... As a result, there is an urging necessity for advanced methodologies to facilitate the use of much needed knowledge included in textual form. Artificial Intelligence (AI) techniques have been employed extensively to enhance information models, document integration, and inter-organizational systems in construction engineering and management, through a variety of automated and semi-automated tools [11]. Text mining methodologies, document clustering techniques, controlled vocabularies schemes and web based models are some of the techniques being utilized to perform the above mentioned tasks [3].

IV. RESEARCH LINES

A. Legal

1) Expert Systems

Expert systems can be defined as AI modeling technique that utilize a set of predefined rules to derive a prediction. The rules are coded into a computer system in the form of "if-then" logic or decision trees. Within the system, rules are evaluated in a successive manner and a final prediction is made based on the combined assessment of all rules. One of the earliest efforts in the construction industry was an expert system under the name of DSCAS to provide legal guidance in relation to Differing Site Conditions (DSC) claims [12]. The system was designed based on knowledge pertinent to the Federal Government Standard form General Conditions (2B-A, GP-4). DSCAS included 22 legal modules, each of which included a set of questions with a "yes/no" answer. Each question is crafted based on legal clauses identified in the aforementioned standards and after detailed deliberations with claim specialists and construction attorneys. The final outcome of the system is whether a claim, on the grounds of DSC, has a likelihood of entitlement or not. In further development for the DSCAS, [13] developed knowledge based expert system titled Claim Expert Knowledge System (CEKS) in the same domain of DSC analysis to aid inexperienced legal advice seekers. The developed system was based on four concepts (1) the Federal Government Standard Form 23-A (Rev. 4-75) was chosen as the binding contract between the different involved parties; (2) the system was based on the owner's prospective when deciding on the entitlement of a claim; (3) the system is intended for technically competent personnel supervising the contractor's performance with a minimal legal knowledge; and (4) the right of entitlement of a claim is only based on expressed contract language and not any other implied rules or laws. CEKS was tested and validated against 13 DSC cases which appeared before a Board of Contract Appeals (BCA). Its prediction capability has proven to be similar to the decisions of the BCA. Following the success of expert systems in this domain, the US Army Construction Engineering Research Laboratory (USA-CERL) developed another expert system to evaluate DCS claims under the title of Claim Guidance System (CGS-DSC) [14]. The system was composed of 13 evaluation modules that were created based on the DSC clause of the Federal Acquisition Regulations Contract (FAR-52.236-2). The system prediction was to classify a claim into one of 6 categories, namely "(1) Very poor chance;

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(2) Poor chance; (3) Difficult to decide; (4) Fair chance; (5) Good chance; and (6) Excellent chance" [14]. In a more recent development, a system was created for the evaluation of the best resolution mechanism to be adopted by a contractor in relation to commencement delay claims. The system utilized decision trees and probabilistic calculation methods in predicting the most cost effective alternative among litigation, relinquish of right, and amicable settlement [15]. Although these systems have accomplished advancements in the legal domain, they have not achieved a wide acceptance due to a major short coming, that is they assume that it is possible to define all rules pertinent to a specific domain problem within one model [16], [17]. As a result, expert systems are perceived to be appropriate for a much localized problem scope.

2) *Artificial Neural Networks (ANN)*

Such aspect has opened the horizon for other methodologies like Neural Networks. As stated in [18], Neural Networks have the ability to analyze complex and incomplete data as well as identifying existing patterns that are implicit to human analysis.

Artificial Neural Networks (ANN) was utilized to model judicial reasoning. As in [19] ANN system was created to predict the outcomes of construction litigation cases from Illinois Circuit Court. The system achieved a prediction precision of 67% while employing a set of 43 input factors (ranging between parties involved, contract type and conditions, project changes … etc). On the other hand, the output was namely, the winner of the case either the Contractor or Owner. References [20] and [21] implemented a particle swarm optimization (PSO) model to train the perceptrons of an ANN system in an attempt to predict the outcome of construction litigation cases in Hong Kong. Similarly, the system utilized a set of 1105 of construction cases that were predefined by 13 input features and 1 output feature [20]. The model achieved a prediction precision of 80%. In [21] a higher prediction rate of 83% was attained. The new system augmented the PSO earlier model with Levenberg-Marquardt (LM) algorithm to benefit from its global search capability. ANN methodologies have proven to be strong predictors in this domain. However, they require extensive training stages. As a result of such high computational cost, researchers have attempted to use other AI techniques. One of the most promising in this field is Case Based Reasoning (CBR). Reference [22] defines CBR to be different from Expert Systems and ANN on a fundamental level, that is, the knowledge required for making prediction is extracted from lessons learned from previous similar cases.

3) *Case Based Reasoning (CBR)*

The literature in the fields of AI and KM highlight the advantage of CBR due to its (1) ability to accommodate missing data; (2) ability to handle more than just numeric data; (3) dependence on implicit human knowledge existing in lessons learned; and (4) no need for continuous maintenance and knowledge augmentation.

Reference [23] provided one of the first and most pioneering case based reasoning (CBR) tools HYPO. It was created to assist attorneys in building arguments about actual cases in the area of trade secret law. The system utilizes a set cases stored in its Case Knowledge Base (CKB) to derive an argument. It builds a claim-lattice of all the cases in the CKB that are relevant to a current case, by making "factual comparisons of cases relative to the problem situation and determine the legal significance in comparisons in terms of arguments about the problem situation" [24]. The pioneering aspect of HYPO is that it provides: (1) factual arguments in favor of the case in hand supported by similar cases in its CKB; (2) counter factual arguments to the case in hand supported by similar cases in its CKB; (3) suggestion of combination of facts for new hypothetical arguments that might provide new prospective for attorneys supported by similar cases in its CKB. However, [25] pioneered the use of CBR systems for litigation prediction in the construction domain. The system implemented a CBR development tool named ESTEEM and the 102 cases from Illinois Circuit Court were augmented with an additional 12 recent cases for testing purposes. The prediction precision was enhanced to 83%. A higher prediction precision of 84% was attained by [26] through adopting a CBR reasoning approach to predict the outcomes of construction litigation cases in Hong Kong. In more recent researches, [27], [28], and [29] developed construction legal decision support systems for the prediction of DSC Litigation outcomes through CBR. The adopted research methodologies utilized factors extracted from New York Federal Court cases. The factors used for verdict prediction ranges between 13 and 23 covering project related items as well as legal concepts upon which judges base their judgments. The developed models attained prediction accuracy of 96%.

4) *Hybrid Systems*

Furthermore, hybrid systems were investigated by researchers in an attempt to improve the prediction precision. HELIC-II models legal reasoning using two engines, a case-based engine identifies similar cases and extracts legal concepts from them, and a rule-based engine uses the legal concepts and the current case's facts to infer all possible legal consequences [30]. CABARET [31], GREBE [32], and Anapron [33] are hybrid systems that combined rule based reasoning with case based reasoning techniques for prediction purposes. CARMA [34] and IBP [35] are algorithms for the prediction of litigation outcomes. In 1995, ANN was utilized to provide the Hybrid Integrated Legal Decision Assistant (HILDA) tool to extract legal knowledge and predict litigation outcomes concerned with the question of "unjust" contracts based on the Contract Review Act 1980 [36]. HILDA integrated similarity measures of RBR and CBR methods as well as the patchy domain theory presented in the legal domain. Legal rules are implemented through ANN to categorize cases in question either for plaintiff, against

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plaintiff, or undecided. Cases that fall within the undecided region are then tested with the CBR component to fit it to one of the other two categories. Reference [37] combined the SMILE system with IBP system developed in 2001 and 2003 respectively in a hybrid system to achieve higher prediction rates. The attained results were promising but indicated that further research is needed in the field of NLP. Furthermore, in 2001 El Hadi developed a statute base Information Retrieval Case Based Reasoning (IR-CBR) hybrid system that implements natural language description of actual situations as its input to retrieve related cases to enhance prediction of litigation outcomes in Bankruptcy Case Law [38]. In 2005, Arditi and Pulket enhanced their earlier studies of litigation prediction in Illinois court cases through the use of boosted decision tree (BDT). They augmented their earlier data base of cases with newly introduced 18 cases that were filed in the period between 1990 and 2000. In this research, a boosting algorithm (ADABOOST) was utilized with decision tree algorithm through a software titled SEE 5. As stated in [39] "The conclusions indicated that ADABOOST can be used in many settings to improve the performance of a learning algorithm. When starting with relatively simple classifiers, the improvement can be especially dramatic, and can often lead to a composite classifier that outperforms more complex "one-shot" learning algorithms". The main advantage of this system over ANN and CBR is that the boosting algorithm works as a plug-in program and helps the primary learning machine to reduce the error rate by repeating decision tree learning for a number of trials and by focusing on the attributes that have effects on error rates. The adopted research methodology achieved a prediction accuracy of 90%, which as illustrated in [39] is helping "create a dispute-free construction industry". In addition, in 2007 Chen and Hsu developed an ANN-CBR model for the prediction of the outcomes of construction litigation cases initiated due to change orders disputes [40]. The model (HACM) combined two algorithms namely, ANN and CBR to achieve a prediction rate of 84.61%. The hybrid model constituted cases gathered from Supreme and Appellate courts over 48 states and districts in USA. They were characterized based on 23 input features, 6 of which are related to project data and 17 were change order related. Research on the prediction of litigation outcomes was not only performed by researchers in universities. Its significance has captured the interest of Government institutes like Donald Berman Laboratory for Information Technology and Law in Australia over the years. In 1991, Donald Berman Laboratory for Information Technology and Law provided a hybrid object oriented rule based system named Intelligence Knowledge based Legal System (IKBALS) to decide upon worker compensation in work care cases in Australia. The second version of the system IKBALSII augmented the rule based reasoner with CBR and information retrieval algorithms to enhance its performance [41]. In 1995, Donald Berman Laboratory for Information Technology and Law built the Split-Up expert legal system that provided advice under the Australian Family Law in relation to property distribution. The Split-Up system is a rule based/ Artificial Neural Network (ANN) system derived from factors attained from thorough investigation of the governing legal factors with domain experts [41].

B. Civil, Architectural, and Construction Engineering and Management

The success of CBR systems in different domains contributed to the birth of its use in the engineering field. Construction Engineering is a very dynamic field. Decisions in this field are influenced by factors that vary from one project to the other like project size and complexity. These factors may influence decisions concerning the involvement of diversified parties with different specializations, site conditions, contract type and conditions, and project location …etc. [42]. Decisions of this nature are highly unstructured and no clear rules are available to provide a clear basis for making them. Consequently, decision makers employ previously acquired knowledge through experience and similar cases. This property made construction a very prominent field for the use of CBR [43]. The rest of this section is dedicated to provide a literature review for the use of CBR in the fields of Structural, Architectural, and Construction Management engineering.

1) Architectural/Civil Engineering

CBR had been used within the design field to facilitate re-use of architecture and structure designs. As defined in [44], architecture is a process of creating a fully developed solution in the form of building designs and specification from an idea. Furthermore, the concept of quality in architecture design cannot be explained in words, thus it is hard to create a rule based system within this domain. "Consequently, traditional architectural design education makes extensive use of architectural cases" [45]. This aspect of design problems initiated research that aim to utilize CBR as an aid to the design problem. CBR has been utilized by adopting previously tackled problems to solve new paradigms after adjusting them to the characteristics and needs of the new problem in hand. As highlighted in [46] a CBR architectural design system was developed under the name of ARCHIE in 1992. CADSYN and DDIS are structural design system proposed by Maher and Zhang [47] and Wang [48] respectively. Reference [45] provides one of the most successful systems named Architecture Case Based Design System (ACABAS). CBDs are a specific type of CBRs that have a wide spectrum of capabilities ranging from generating "a description of existing buildings or designs in the case base" to the development of "a complete building specification" for a new design problem [44]. The ACABAS system utilizes an object oriented database which stores information about the different cases. This database includes CAD models that are precisely generated for the CBD system. A developed pre-processor (Mod-4) was designed for this function. It accepts geometric description of the building and

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requires further information like room labeling, materials description, and building design specifications to generate object database and graphical representation of each case. The later constitutes a set of unstructured information like scanned images, text description of the building and its location, interview with the occupants, energy bills, acoustical and thermal problem areas, textual description of repairs history … etc. Normative and Functional constraints are further identified as parameters of each case. When a new design situation is introduced to ACABAS, it retrieves the most similar case and implements adaptation mechanisms to fully satisfy the parameters of the new problem. Topological and dimensional discrepancies are identified as the first step of adaptation. In case of discrepancies, adjustments are applied based on transformation rules that are built into the system while maintaining the normative and functionality constrains un-violated. ACABAS undergoes an iterative process until all transformations are applied without violation of the defined constrains. In addition, [49] employed CBR in building defect diagnoses through the development of PAKAR. As indicated in [50], Flemming and Woodbury built up the SEED project, which utilizes case-based reasoning to provide computational support for the early design phase. In [51] a hybrid system was developed to determine errors in the fabrication of steel bridges. The developed system integrates case based and rule based modules. The system which was developed to provide a formalized methodology for repair of fabrication error had a case base of 112 cases of previously experienced errors and corrective actions gathered entirely from KDOT projects. Cases were classified into 13 sub modules based on the type of fabrication error as follows: mis-located holes (33 cases), mis-cut members (20 cases), nicks and gouges (13 cases), mis-located members (10 cases), mis-shaped holes (8 cases), edge distance (6 cases), laminations (6 cases), mis-aligned members (6 cases), mis-attached members (4 cases), size error (2 cases), stress fracture (2 cases), end distance (1 case), and partially drilled holes (1 case). Evaluating the use of CB-BFX module alone yielded a precision of 82%, which was an impressive advancement over the use of the rule-based module that attained 63%. The combined hybrid system, using both modules, achieved an overall success rate of 91%. Reference [42] stated that the complexity of modern construction projects leads to the use of increasingly sophisticated construction methods and requires extensive interactions between diversified parties. As an example of that, facilitated Computer Aided Systems Architecting CASA, a technique combining systems and requirement engineering approaches with AI, is growing rapidly to cope with the market competition [42]. In [52] a case-based approach to be augmented with CASA to support reusability of designs of existing systems in determining the architectural requirement fulfillment of new components under design was developed by Praehofor and Kerschbaummayr. Retrieved solutions by CASA are accompanied by a degree of fulfillment factor (DOF) between [-1, 1] signifying the extent of similarity and required adaptation to new paradigms. To further explain the DOF concept, a DOF value of:

- 1 means full fulfillment of the new system requirements and can be adopted as a solution with no modifications.
- 0 to <1 means partial fulfillment of the new system requirements and can be adopted as a solution with some architecture tailoring.
- -1 to <0 means does not fulfill the new system requirements and cannot be adopted as a solution.

CASA employs predefined language and lexical structures, which are domain dependent, with object oriented structure to define new components' properties and requirements and had showed significant success in transportation and material handling design [52]. Likewise, in 2005, Sirca and Adeli developed an intelligent hybrid decision support system (IDSS) that utilizes CBR and ANN to assist bridge engineers to semi-automatically convert the rating of bridges from Working Stress Design (WSD) method to Load Resistance Factor Design (LRFD) method [53]. According to [53], "in 1995, the Federal Highway Administration (FHWA) required that all bridges, regardless of the design method used for the original design, be based on the load factor design (LRFD) method". However, steel bridges originally rated using WSD had missing information that made the adoption of LRFD hard. As an example, a major piece of information that is required for the conversion, which is not part of the WSD design method, is the lateral bracing spacing of girders [53]. Such an aspect made the rating conversion very hard and labor intensive, for an engineer has to use his knowledge to make decisions about the lateral bracing spacing from the design data available from the WSD design method and the design guidelines utilized at the period of designing the bridge [54]. As a consequence, the expert system was developed to assist in deriving the missing data about lateral bracing requirements from similar cases for bridges under the jurisdiction of ODOT. The system employed structure analysis files attained from AASHTO Bridge Analysis and Rating System (BARS-PC) as its case based knowledge database. CBR is utilized to define a similar case and attain input data that are employed in the ANN, a system that was developed in an earlier research in [55], to define the required missing parameters of section properties description. After attaining all required parameters, the BARS-PC data file is updated and saved. The model's database included a set of 39 cases that are used to derive all missing information. As stated in [53], proper identification of the bracing is highly dependent on the year at which a bridge was built. Based on that, weights are assigned to each field based on its relevance. These data characteristics as well as assigned weights to each field are utilized to define the similarity between a new case and those stored in the database. Similarity measures of cases are based on linear weighted similarity functions which are then ranked using Nearest-neighbor matching to define the most similar case. When a matching case is defined, its lateral

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bracing data are retrieved from separate database and inputted to the ANN to decide on the conversion required.

2) *Construction Engineering and Management*

In addition to Architectural and Structural design, CBR approaches were implemented in variety of construction engineering management problems including construction duration estimation, productivity estimation, cost of building estimation, bid decision making, procurement criteria selection, construction negotiation methodologies, and contract strategy formulation. As identified in [56] and [57], Project scheduling is one of the key factors in determining the success of construction projects. Interest in developing and formalizing good scheduling practices has always been of significance in the construction research community. Furthermore, [58] highlights that successful scheduling requires judgment about variety of interrelated factors and criteria concerning diversified and characteristically conflicting set of constrains. Over the last decade, there has been an increasing interest in techniques that exploits previous experience in developing and modifying project schedules [57]. Reference [59] provided a CBR approach in CABINS for iterative schedule revision in job shop schedules. "CABINS is composed of three modules (1) an initial schedule builder based on constraint-based scheduler; (2) an interactive schedule repair module, and (3) an automated schedule repair module" [59]. Schedules developed in the first module are not optimized due to the absence of the complete knowledge of the scheduling domain model and user preferences. To attain an optimized schedule, CABINS implements the second and third modules through a CBR approach that adopts previous optimizations in the case base. "CABINS gathers the following information in the form of cases through interaction with a domain expert in its training phase.

- A suggestion of which repair heuristic to apply: a user's decision on what repair heuristic to be applied to a given schedule for quality improvement.
- An evaluation of a repair result: a user's overall evaluation of a modification result. The evaluation categories currently employed are 'acceptable' and 'unacceptable'.
- An explanation of an evaluation: when a user evaluates the modification result as unacceptable, she/he indicates the set of undesirable effects that have been produced. The explanation given to CABINS consists of the numerical rating of each identified effect." [59].

In the optimization process, CABINS identifies vulnerable activities based on the user's preference criteria. The system then works in an iterative manner and optimizes schedule activity by activity and not the whole list at once. The most similar modification requirement retrieved from the case base using K-Nearest Neighbor is adopted for the first activity. The outcomes and effects on the schedule corresponding to the user's preference criteria are identified and presented to the user. If the optimization is accepted, the case base is enriched with this particular optimization. On the other hand, if the optimization is not accepted, the user is asked to provide a justification that is tagged with the optimization process in the case base and other iterations are performed. Amicable settlement through negotiation is another construction problem that entails extensive expertise and knowledge of similar cases. In 1996, a CBR intelligent support system to construction negotiation was provided. "This model has been implemented in the MEDIATOR, a computer program that utilizes previous cases as a basis for addressing new problems. In contrast to conventional expert systems (ESs) that use compiled knowledge in problem solving, the system selects similar cases to help in solving a given negotiation problem" [60]. Cases in the case-base are represented in terms of 6 factors: "(1) case number and indexing keywords, (2) situational description addressing the background of the negotiation, (3) negotiating parties, (4) disputant issues and goals, (5) final settlements, if it is successful, or unsuccessful, and (6) negotiation history" [60]. MEDIATOR allows each of the parties to illustrate their "issues and goals" which are used as factors for retrieval of similar cases. The solution of the most similar case is adopted as a solution to the new situation, which could be accepted, rejected, or employed to derive new users' goals. As stated in [61], CBR-CURE a case-based reasoning system to assist owners decide on the feasibility of a design through conceptual estimates of construction activities was developed by Yau and Yang. CBR-CURE was created using ESTEEM, a Window based tool for developing CBR systems, which is commercially available through Esteem Software Incorporated since 1991. The case database constituted of 60 hypothetical projects. The cases are identified by 13 input features, among which are project's name, start and finish dates of the project, and 4 output features defining the duration, equipment cost, material cost, and labor cost of the project. The system input interface allows the user to assign weights for each of the 13 input features. These weights are utilized to determine case similarity. The interface also allows the user to define a minimum similarity value above which cases are deemed similar and are retrieved. The duration and cost of a new case is determined by using adjustment factors that are built into the system to modify the values attained from a retrieved case. Reference [62] tackled the profitability problem in the construction domain through the development of a hybrid model that combines support vector regression (SVR) modeling with a principal component analysis (PCA). Their analysis was based on data gathered from a set of commercial building projects. The focus of the research was related to early planning tasks within a project. Consequently, a set of 64 factors associated with the aforementioned construction stage were identified and used as the input parameters of the developed model. Lee et al. created an automated tool using matrix laboratory (MATLAB) to improve the uncertainty of activities' costs to estimate the best-fit probability distribution of cash flows, overdrafts and profit [63]. References [64] and

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[65] proposed an automated Latent Semantic Analysis models with Support Vector Machines to assess cost estimates based on error ranges to improve construction cost decision making. Furthermore, the dynamic nature of the construction bidding decision making process also led investigators to utilize the power of CBR systems within this field. [43] developed a system that assigns markup levels to construction projects under the name of "CASEBID". The developed system attempts to maximize the profit of new project under bidding based on similarity measure to previously performed bids. The assessment is performed based on a group of internal and external factors that are competition and risk related. In a comparative study CASEBID outperformed the conventional statistical approach. "It posed 55% bid wins, yielding an average 7.4% expected profit compared to 41% bid wins, yielding an average 6.15% expected profit in the case of the latter approach." [43]. Similarly, Mahfouz developed a productivity estimating model through Machine Learning methodologies [27]. The research study focused on steel structures related activities. It utilized 28 factors and data gathered from 59 activities. The factors ranged between project, company, activity, and weather related. The adopted research methodology developed and compared 2 modeling algorithms namely Support Vector Machines (SVM) and Naïve Bayes (NB). The research study achieved a prediction accuracy of 70% using NB modeling. As a matter of fact, construction projects include many repetitive and cyclic activities as highlighted in [66]. Likewise, judgment about the best methods and techniques to be adopted for cyclic processes is based on previously attained expertise concerning productivities and technologies. Reference [67] proposed a CBR based estimator (CBE) to predict the productivities of concreting cyclic operations from previous cases. The model consisted of 5 input features and one output feature. "CBE was validated, not only against the performance of past operations (which were not used in the model development), but also against estimates provided by a professional construction planner. The model was found to provide more precise and consistent estimates than the planner, with 90% of the estimates being within a 10% relative error of the observed value" [67]. In such a dynamic environment as that of the construction industry, procurement decisions are crucial to the success of project. In such decisions previous knowledge is the corner stone of decision making [68]. Timely deliveries are major aspects of the successful completion of any construction project [69]. Consequently, Companies tend to work with suppliers with whom they had good experience. Researchers have pointed out that the identification and use of a suitable procurement system could contribute immensely to the success of a construction project [70]-[71], and this has been a driving force for the development of various procurement selection approaches. Such dependency on previous experience gives a high potential for CBR approaches. Reference [72] created a model for procurement selection. The developed prototype is not dependent on owner and/or project properties. As stated in [72], these factors are very hard to model based on their wide diversity. As a consequence, the prototype model relates these parameters to their associated factors that can affect such a decision like speed, time certainty, quality, flexibility, risk allocation …etc. For more illustration, if "on-time completion" is a key objective of the client, not only the speed but also the time certainty, flexibility, and quality are considered during the evaluation process. The evaluation factors were derived from a methodical investigation of the different procurement selection criteria techniques and semi structured interviews were conducted with managers of five major client organizations in Australia (four governmental and one private) experienced in construction procurement selection. One of the main construction problems that is normally resolved using previously gained knowledge and managerial expertise is contract strategy formulation. In fact, it is inherently, too complex, too personal, and too dynamic to be modeled in a fully automated manner [73]. Despite this difficulty, CBR approaches can be utilized to facilitate automation of the use and reuse of these expertise. As shown in [74], Chau and Loh developed a prototype of a decision support system, CB_Contract, which exploits CBR approach for contract strategy formulation. The system incorporates the four main components of contract strategy formulation, namely work packaging, functional grouping, Contract type, and award method. It further integrates these components with other crucial factors, such as "form of contract, currency and timing of payment, nomination of subcontractors by the client, type of specifications (performance or construction method), penalty scale for liquidated damages, and occasionally the provision of contractual motivation and incentives" [74]. ReCall, an interactive human machine system, was used for the development of CB-Contract. "The case retrieval process takes place within the ReCall environment using inputs from the user. Thereafter, the user will carry out the necessary adaptation to the cases to formulate the contract strategy for the current project based on three important considerations: (1) robustness of the retrieved set of sub strategies; (2) compatibility of the sub strategies; and (3) effectiveness of the alternative solutions." [74]. to assist the user in making such decisions, each case is associated with a brief description of the project. The adopted method and the case parameters are then augmented into the knowledge base of the system for reuse in future models. In some of the most recent studies, a group of researchers employed statistical modeling for the assessment of markup value assignment to construction project [75]. The adopted research methodology utilized 32 factors related to site characteristics, project complexity, level of document details, contractor and owner financial capacity, contractor's team experience, and competition level. The developed model through Ordered Probability technique estimates the appropriate markup percentage to be assigned to new projects based on the defined factors with a prediction accuracy of

67%. In further development of this study, Mahfouz and Jones [76] developed an automated model through CBR and the identified factors. The highest prediction accuracy achieved was 58%.

V. DISCUSSION

From the literature in this domain, it was noticed that there is still work to follow in this area. It is apparent that AI research in the legal and construction domain has been progressing along similar lines. An important aspect in both of these domains is that they rely heavily on textual material expressed in human language: legal references and judicial opinions in the legal domain, contract conditions, specifications, correspondences, etc. in the construction domain. This creates a strong need for well defined methodologies that are capable of effectively analyzing textual material and efficiently retrieving pertinent information from them. Besides, the accuracy of the output of an automated system is largely dependent on the availability of reliable information about the attributes used to define the training cases. As stated in [39] “Finding a complete and reliable set of training examples is difficult in construction litigation cases”. The use of natural language processing techniques NLP can enhance and facilitate the use of construction litigation prediction models. Automatic cases classification and knowledge extraction can be improved through NLP techniques [77]. Although the research endeavors discussed within the body of this paper have achieved far stride to assist the industry in utilizing and extracting data from existing documents, these is still a lot to be done to achieve their full potential. This could be attributed to the followings:

- Access to large databases: The majority of the addressed researches within the paper are performed on small scale to solve a specific problem or to prove a concept. The conversion of some of these models into commercial systems requires access to massive data and information as well as abundant number of projects to develop a comprehensive tool that encompasses all aspects of a specific area. Collection and gathering processes of such data is cumbersome due to one or more of the following factors, namely (1) the extensive time needed, (2) reluctance of some firms to provide it, (3) poor existing data management systems, and (4) the demand for substantial financial support.
- Interoperability: Since the development of a comprehensive tool would require the integration of more than one system, interoperability of large scale database systems in a dynamic environment represents a persistent challenge.
- The need for a cultural change: To a great extent, there exists a gap between the research developments and implementation within the construction industry. According to [78] the construction field is behind others, such as aviation and biomedical in the implementation of technology to increase performance and productivity. Furthermore, Koebel highlighted that the future of the construction industry is in need for firm driven innovation efforts [79]. Although that over the last decade there has been some adoption of new technologies like Building Information Modeling, it has been highlighted that some professionals believe that the majority of the research work lacks the applicability aspect. This notion is further supported by the fact that the construction industry is heavily dependent on the human intervention from labors, supervisors, managers, to decision makers. References [80] and [81] relate this to the highly dynamic nature of the construction industry, increased complexity of the projects, and varied site conditions. “Complexities among residential builder firms also contribute to adoption failure” [82]. As a result, the idea of automated decision support system is hard to grasp. “Currently, most builders consider innovation resistance good business practice.” [82].

VI. CONCLUSION

This paper attempts to presents a comprehensive review of Knowledge Management (KM) research efforts in the A\E\C domain and highlights the challenges hampering its full integration into the market. It is evidently clear from the reported research studies that CBR approaches are very helpful in utilizing previously learned experiences to solve newly encountered ones. In contrast, the success of model based and rule based approaches is hampered by the fact that they are dependent solely on the computational efficiency, and the assumption that there exists a strong domain model. However, the success of CBR approaches comes at a higher cost of manually extracting information pertaining to the different cases. A possible solution to this problem can be obtained through Artificial Intelligence (AI) and Natural Language Processing (NLP) techniques. Although these studies have achieved major developments in their respective domains, their adoption into the industry is challenged by the need for access to large databases, culture change, and resolution of interoperability problems. That being said, over the last decade there have been a number of initiatives to resolve the aforementioned challenges. An aspect that is much needed for guarantying a successful future of the construction industry.

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AUHTOR'S PROFILE

Tarek Mahfouz is Associate Professor of Construction Management at the Department of Technology, Ball State University. He earned Doctoral Degree (Ph.D.) in Civil Engineering with a specialization in Construction Engineering and Management from Iowa State University (ISU), Masters of Science (M.S.) and Bachelor of Science (B.Sc.) in Construction Engineering and Management from the American University in Cairo.

Over his years of professional and academic work, he has attained expertise in areas of Knowledge Management (KM), Machine Learning (ML), Decision Support (DS), Intelligent Information Modeling, Statistical modeling, Data Sensing and Analysis (DSA), Planning & Scheduling, Construction Law, Claims, and Construction Finance. Dr. Mahfouz has a strong record of publication in peer-reviewed journals and conference proceedings including but not limited to Journal of Computing in Civil Engineering, International Journal of Engineering Research and Innovation (IJERI), Construction Research Congress, International Workshop of Computing in Civil Engineering and Canadian Society of Civil Engineers Annual Conference Proceedings.

Dr. Mahfouz is an Associate Member of the American Society of civil Engineers (ASCE), a member of the Association of Technology, Management, and Applied Engineering (ATMAE), Construction Research Congress (CRC) committee member, ASCE Data Sensing and analysis (DSA) committee member, and ASCE Technical Council for Computing and Information Technology (TCCIT) committee member. He is currently serving as the Vise-President of ATMAE-Construction Division and the secretary of the American Arab Association of Engineers and Architects Indiana Chapter. Dr. Mahfouz has recently been selected one of the awardees of AGC Education and Research Foundation 2014 Faculty Internships. He is an editorial board member of multiple journals including American Journal of Computer Technology and Application, Computational Science and Engineering Research Journal, and Research Journal of Engineering and Computer Innovation among others.

His activities have been recognized through multiple awards like (1) ASCE 2013 Outstanding Reviewer for the Journal of Computing in Civil Engineering, (2) ASCE 2010 Outstanding Reviewer for the Journal of Construction Engineering and Management, (3) Green Initiative Award by the Council On The Environment (COTE) at Ball State University, and (4) 2011-2012 Department of Technology Outstanding Teaching Award,