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A Proposal for Research on the Application of AI/ML in ITPM:
Intelligent Project Management

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ABSTRACT

According to the market research firm Tractica, the global artificial intelligence software market is forecast to grow to 126 billion by 2025. Additionally, the Gartner group predicts that during the same time as much as 80% of the routine work, which represents the bulk of human hours spent in today's project management (PM) activities, can be eliminated because of collaboration between humans and smart machines. Today's PM practices rely heavily on human input. However, that is not the optimum use of the human project manager's intuitive, innovative, and creative abilities. Many aspects of a project manager's work could be managed by machines that utilize AI/ML approaches to address nonroutine and predictive tasks. This paper describes IT project management (ITPM) processes and associated tasks and identifies the AI/ML approaches that can support them.

KEYWORDS

Artificial Intelligence, Complex Tasks, Machine Learning, Project Management, Project Manager, Tasks

INTRODUCTION

Project management (PM) practices are necessary to ensure the success of an organization's strategic and performance goals in the context of a changing information technology (IT) landscape. Organizations need to be flexible and adaptable to change while practicing a disciplined approach to managing project success. Various PM standards and capabilities have been proposed to address the turbulent dynamics caused by changing technology (Kanakaris et al., 2019; Pospieszny et al., 2018). The advent of commoditized artificial intelligence (AI) services has created much buzz among industry professionals and academic practitioners. While the basis of machine learning (ML) is to use machines with algorithms to learn and adapt through "experience," AI refers to a broader idea where machines can execute tasks "smartly" which otherwise require "human intelligence." AI applies computer vision, ML, deep learning, and other techniques to solve concrete problems.

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Today's PM practices and processes rely heavily on human input. All data about projects are collated, organized, and consumed by human beings. However, this is not an "optimum" use of the project manager's intuitive, innovative, and creative abilities. Schoen (2017) predicted that, by 2030, as much as 80% of the routine work, representing the bulk of human hours spent in today's PM processes, might be eliminated because of the collaboration between humans and smart machines. The goal here is to allow project managers to work on complex problem solving and sensemaking while routine PM work gets managed by smart automation (Frensch & Sternberg,1991).

The notion of *intelligent project management* captures these ideas wherein routine tasks/processes would be automated using AI/ML to reduce human intervention, while the human project manager professional spends more time on innovative, intuitive, and creative tasks. Additionally, the human project manager would utilize AI/ML tools and techniques to augment their decision-making capabilities. Thus, AI/ML can be utilized to automate tasks which require learning as well as tasks which are relatively straightforward and which have a clear and predefined sequence of steps (i.e., routine tasks). Routine PM tasks are currently executed by a human, but these could conceivably be transitioned to a machine. This type of automation has been happening in businesses for decades, particularly in manufacturing with robotics, just-in-time inventory management with electronic data interchange, and, recently, in the service sector using robotic process automation (RPA). However, despite the enormous advancements in AI/ML, very little progress has been made in the PM discipline to leverage AI/ML capabilities in the practice of the profession (Khazanchi, 2018; Winter et al., 2006). Over the years, PM researchers have concluded that project success (and failure) is directly affected by the nature of the task associated with PM processes (Rolstadås et al., 2014). Therefore, in this paper the authors investigate the overall PM processes and their inherent tasks and illustrate how they are amenable to the application of AI/ML approaches.

PROJECT MANAGEMENT

PM processes are used to achieve project goals in a certain amount of time and budget by following guidelines that allow the use of knowledge and skills to be incorporated efficiently (Varajão et al., 2017). In this context, for example, the PM body of knowledge (*PMBOK® Guide*) prescribes a global standard for PM professionals (Project Management Institute, 2017). In this paper, the authors use the *PMBOK® Guide* five process groups (i.e., initiation, planning, execution, monitoring, control, and closing) to determine tasks that, in these groups, are conducive to AI/ML approaches (Varajão et al., 2017). Below, Table 1 provides a summary description of these processes (Project Management Institute, 2017).

All the processes in Table 1 incorporate specific tasks that must be completed effectively to assure the success of a project. In the next section, the authors expand on the different types of tasks within PM processes.

Classifying Project Management Tasks

Researchers have used a broad classification of task types, specifying simple tasks and complex tasks (Ackoff, 1972; Rittel & Webber, 1973). A simple (routine) task has clear objectives which can easily be mapped to solutions. For example, "verify stakeholder identification" is a simple and routine task where the goal is well-known. A complex (nonroutine) task requires responses that deviate from common solutions or from previously learned ones (Maier, 1970). In a complex task, the objective is known but the goal is either unknown or there may be multiple goals. Complex tasks differ from simple tasks in the availability of information about the task, the precision of goal definition, the number of variables, the correlation among variables, and time dependencies over the course of achieving the goal to solve a problem (Frensch & Sternberg, 1991). For example, "assure the development of contingency plans to cope with staffing problems" is a complex task. The task is clear if the project team has a clear understanding of the "staffing problems and development of contingency plan,"

Table 1. Description of Project Management Processes (adapted from PMI's PMBOK® model)

PM process stage	Description
Initiation	First phase in the PM life cycle, which contains the layout of the tasks needed to be completed. Processes, such as understanding the expected expenses surrounding the project, will help build a foundation that allows all ideas to be laid out and made clear to all who are a part of the new project. Choices made within this phase determine how the remaining four phases will run as well as how efficient communication amongst management will be.
Planning	The second phase of the PM life cycle. It includes detailed planning to execute the project. Some key activities are requirements gathering, definition of team roles and schedules, and identification of risks and response plan.
Execution	Third phase and most resource-intensive phase. It ensures carrying out the details of the project charter and project plan for successful delivery of the product by following processes and managing resources.
Monitoring and control	This process serves to supervise all project tasks and metrics to ensure that the project will proceed with minimal risk and will meet the planned scope, time, and budget constraints. Also, this process will identify problems, deal with conflict resolution, ensure quality control, and implement control changes. It is significant because it keeps the project on track.
Closing	The last and final phase, which is an important aspect of the risk management cycle of an organization. The goal is to assure project closing activities have been completed, which include the lessons learned report. A lesson learned report enables the documentation of a particular project's challenges and successes. By creating this report, an organization will be able to interpret the data and either repeat the processes or apply changes to future projects. Learning from a completed project will allow for a better understanding of PM and for process improvement, which will also improve risk management.

but understanding how to accomplish the task may not have clear solutions and could depend on the assumptions built into the variables and the prior experience of the project manager.

Accomplishing goals for complex tasks often requires organizational learning (Campbell, 1988; Senge, 2006). To distinguish task complexity in PM processes, in this research the authors adapted Campbell's (1988) typology of tasks: Decision tasks, judgment tasks, problem tasks, and fuzzy tasks. Table 2 provides relevant definitions and examples.

Artificial Intelligence and Machine Learning

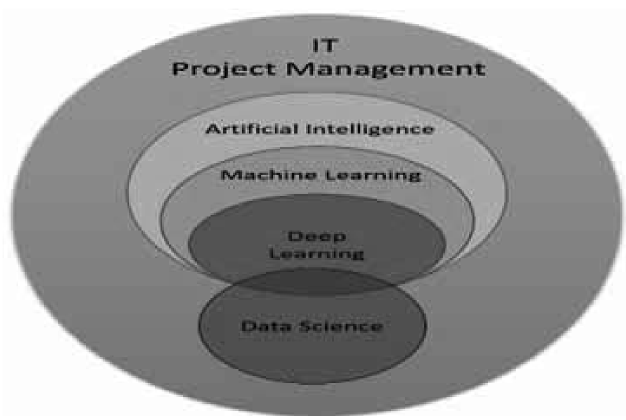
Predictive analytics and learning represent a broad spectrum of techniques that can be used to analyze large datasets to identify patterns which may be used to make predictions about what the future may entail. One such collection of techniques is the broad discipline of AI (Figure 1). AI has become an increasingly popular field of study as its power and potential for predicting future events is being realized. AI approaches can be used to create machines that can behave much like humans to perform tasks related to reasoning, problem solving, perception, learning, and planning. AI techniques also include RPA, language processing using chatbots, and knowledge management/representation. One critical facet of AI is ML, which is a subset of AI that includes algorithms that can learn from data without explicitly being programmed (Goodfellow et al., 2016). Based on the characteristics of data, ML is categorized as supervised, unsupervised, and reinforcement learning.

Supervised learning algorithms use data features associated with target labels, whereas unsupervised learning contains only data features to extract knowledge from the data. Clustering is broadly an unsupervised learning algorithm where regression and classification are popular supervised learning algorithms. Reinforcement learning is utilized when the data are collected and learned by a trial-and-error approach. It is based on a reward system, where the goal of the algorithm is to maximize the reward to learn a good strategy (Sutton & Barto, 2018). When data are large and complex, deep

Table 2. Typology of Tasks (Campbell, 1988)

Task type	Description
Routine/Repetitive tasks	Relatively straightforward tasks have an exact and predefined sequence of steps. Examples: Data entry, project schedules, and cost estimation ,
Decision tasks	Common emphasis is on selecting or identifying an outcome that may have multiple desired end-states. Examples: Technology project data (i.e., automation and learning using emerging technologies such as Internet of things and Internet of nano-things; ML on the edge) and project charter completion.
Judgment tasks	Based on the various information, a prediction needs to be made for future events. Examples: Verifying the requirements to ensure testability and feasibility; conducting a product release review prior to implementation and post implementation.
Problem tasks	To achieve desired end goals, many paths are possible. The main objective of a problem task is to identify the best path to achieve the desired end goals. Example: Continually review progress and set objectives for the next phase.
Fuzzy tasks	This is the most complex task due to the presence of numerous end goals and various ways of achieving each of the end-goals. Example: Cost assessment or risk assessment models using ML amenable to ML techniques–it requires some learning.

Figure 1. Artificial Intelligence



learning uses neural networks to learn the data features (Goodfellow et al., 2016). Automation of repetitive tasks that are monotonous and require less human supervision can either be algorithmically computerized and/or include elements of AI/ML (Kaelbling et al., 1996). For example, RPA could be used for automatically routing PM processes such as project charter completion and project quality assurance. On the other hand, to ensure timely completion of tasks that require human intervention, AI approaches can help by creating bots to send follow-up notifications to individuals whose action is required, and by automatically adding events on employee calendars when their presence is necessary. In contrast, tasks such as project cost or schedule estimation may benefit from the application of ML techniques. Table 3 presents a typology of various ML approaches as well as some of the algorithms employed under each category.

Predictions relating to tasks are generally based on historical data and are constructed by implementing statistical modeling and ML techniques. Organizations can use predictive analytics in

Table 3. Machine Learning Typology and Description (Goodfellow et al., 2016; James et al., 2013; Sutton & Barto, 2018)

ML type	Description	Example algorithms
Supervised learning	Algorithms where data features are associated with target labels.	Linear regression, logistic regression, support vector machine, K-nearest neighbors, decision trees, naïve-Bayes, random forests.
Unsupervised learning	Algorithms without labels and contains only features to extract knowledge from the data.	Dimensionality reduction, K-means clustering, hierarchical clustering, recommender systems.
Reinforcement learning	Data are collected and learned by trial and error approach with reward feedback.	Q-learning, temporal difference, SARSA, deterministic policy gradient.
Deep learning	ML type where neural network are used to learn the data features.	Convolutional neural networks, recurrent neural networks, generative adversarial networks, autoencoders, restricted Boltzman machine, deep belief networks.

several ways, including detecting patterns within a dataset to determining risk by discovering implicit and explicit relationships between different variables. This can be taken a step further, if organizations use these patterns to forecast project success/failure, predict costs or changes in schedules. These mechanisms can be used to increase revenue and decrease operating costs, which is the goal of any organization (Pospieszny et al., 2018).

In the context of ML, the nature of a task is an important determinant to distinguish which AI/ML approach is ideally suited for accomplishing the task. As Table 3 illustrates, AI/ML techniques can be broadly classified as automation-oriented and learning-oriented. ML algorithms can help automate processes, but not all automation problems require learning. Automation without learning is appropriate when the problem is relatively straightforward or routine. These are the kinds of tasks where one has a clear and predefined sequence of steps that is currently being executed by a human, but that could conceivably be transitioned to a machine. This sort of automation has been happening in businesses for decades.

Artificial Intelligence/Machine Learning and Project Management Tasks

Table 4 lists AI/ML techniques that can be leveraged to solve issues relating to various PM tasks/processes. Using the descriptions, definitions, and background information of each PM process from the literature, the authors evaluated the tasks associated with PM processes and suggest AI/ML techniques that can support example issues relating to them. For example, the question "Can AI/ML tools be used to identify risk and create risk response plan?" occurs in the planning phase. Based on the definitions in Table 2, the authors evaluated "identify risk and create risk response plan" as a judgment task. Judgment tasks need information from diverse sources. Similarly, identification of risks requires access and integration of risks-related information across different PM phases. This process can leverage supervised learning models, capable of identifying potential risks based on historical PM data. All the authors of this paper performed this exercise and discussed the coding to reach an agreement. Table 4 provides a summary of this analysis.

Discussion and Implications

The authors' analysis of PM processes suggests that there are many opportunities to leverage various approaches to automation, including applying ML approaches. Among the five PM processes, most planning phase activities can utilize multiple AI/ML techniques, such as unsupervised, supervised, and reinforcement learning. Various AI/ML algorithms can be implemented for the planning phase depending on the activities (Hardesty, 2016). To estimate budgets and schedule, supervised AI/ML techniques, such as artificial neural networks, can be used to develop cost and schedule models.

Table 4. Example Applications of AI/ML to PM Processes

PM process	Example issue and task	Task types	AI/ML techniques
Planning	What AI/ML technique can be used to predict whether a software product will be delivered on time?	Judgement	Supervised learning Reinforcement learning
Planning	Can AI/ML tools be used to reassign tasks based on the staff expertise?	Decision	Supervised learning Unsupervised learning
Planning; Execution	Is it possible to *a priori* predict project failure and propose adjustments to project plans?	Problem	Reinforcement learning
Initiation; Planning	Is it possible to use artificial neural networks and other AI/ML techniques to develop predictive models for estimating factors such as size, effort, resources, cost, and time spent in the software development process?	Problem	Supervised learning
Execution	Is it possible to use AI/ML to effectively analyze team behavior patterns to determine strengths and weaknesses and then develop teams with members with optimal skills? n?	Fuzzy	Unsupervised learning Reinforcement learning
Monitoring and control	Can AI/ML be used to analyze performance data to foresee problems such as overdue tasks or bottleneck tasks?	Decision	Reinforcement learning
Planning; Execution	Can AI/ML tools be used to evaluate project data to advise about resource assignments by identifying who has the skills and experience necessary to perform a task, considering the current situation?	Fuzzy	Unsupervised learning
Planning	Can AI/ML tools be used to assess the risks involved in various software development life cycle?	Fuzzy	Supervised learning Reinforcement learning
Initiation	Can AI/ML tools be used to perform PM activities such as obtaining executive signoff, check project scope statement for completeness, verify stakeholder identification or support vendor solicitation and selection?	Routine	RPA and potentially supervised learning

If significant scope changes occur, these techniques will help the machine learn from the data to proactively facilitate the development of a revised cost and schedule model.

The next two PM processes which can benefit from AI/ML techniques are initiation and execution. Most of the activities of the initiation phase are repetitive (i.e., routine tasks). Most PM routine tasks are procedural and can employ AI-based tools such as RPA, chatbots, wrike (https://www.wrike.com/), clickup (https://clickup.com/), polydone (https://www.polydone.com/), and clarizen (https://www.planview.com/products-solutions/products/clarizen/). AI chatbots can be used to notify users when a deadline is approaching and remind them when a task assignment is past due. Some of the execution phase activities can fall under the problem or fuzzy task category. The PM tasks that are either problem or fuzzy are more complex and require supervised and reinforcement learning AI/ML techniques. Utilizing AI/ML learning, project managers can effectively communicate with their employees and oversee the overall quality, progress, and work issues (Schmelzer, 2019). For example, these predictions could give accurate updates to project managers about how well the software development plan is being executed and the prediction of when the plan will be completed.

The categorization in Table 4 is not comprehensive, but is meant as a starting point to begin exploring how AI/ML can be used within the context of PM. It is possible that some of the processes may fall under more than one task category. For example, "project charter completion" can be a decision task as well as a problem task. If the emphasis for project charter completion is on choosing the various attributes of the project that optimally achieves multiple desired end-states, it will be a decision type task. On the other hand, since a project charter process is well-specified and the desired outcome is known, it is a problem task.

The authors acknowledge that the adoption of AI/ML approaches in ITPM requires certain basic prerequisites. First, data about the projects are essential for anything predictive. Although many firms keep project history records, it is difficult to access firm level project data across time that are clearly documented and well organized. This makes it even more important for PMs to consider spending the resources to keep track of lessons learned reports and retrospective reports on projects. It is important to note that in AI/ML applications it is well established that predictions and classifications are as good as data. These constraints in the use of AI/ML may dissuade project managers from employing AI/ML for mission critical processes and tasks such as risk assessment due to the complex nature of the task and the element of human experience and intuition needed to solve it. However, these are quite amenable to ML and would require project records of prior models of risks.

CONCLUSION

PM is an extremely important practice involving decision making under uncertainty at various stages. Project managers' knowledge, intuition, and experience, coupled with effective tools and guideline, can result in project success or failure. In the planning stage of PM, AI/ML approaches can be utilized to create schedules, allocate resources, and create risk management solutions. During the execution stage, project managers can use an AI/ML tool, predictive analytics, to make accurate predictions of project completion based on their current work status. These are just two of the many examples of how AI/ML can play a major role in the planning and execution stages of PM.

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