Explainable Artificial Intelligence (XAI) in Project Management Curriculum: Exploration and Application to Time, Cost, and Risk

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**Introduction**

Project Management (PM) has been a key process and practice adopted and implemented to achieve management objectives for both government and private entities. The processes and technologies used in project management since WW II have seen new tools and techniques. In the information technology era, since the mid-1990s, tools for initiating and tracking a project to its expected completion (e.g., MS Microsoft Project) have become commonplace. The explosion of projects and the need to establish a more standard process resulted in the formation of the Project Management Institute (PMI; www.pmi.org) in 1969 which is now an international organization. Universities, colleges, and technical schools have established strong curriculums for teaching project management with PMI providing various certifications.

All the current teaching curriculum is mostly focused on PM technology developed some decades ago with new tools helping to automate them. The advent of Artificial Intelligence (AI) and its use in PM provide new opportunities for prediction and better results. This paper will investigate and demonstrate the adaptability of AI for PM, and how the teaching curriculum can be changed to help introduce the AI for better project performance. PMI, from a professional perspective, is also beginning to discuss the use of AI.

This paper will cover two current teaching methods followed by details of AI for PM and its teaching. First, we discuss a common teaching method that uses an engineering deterministic framework to present Performance Evaluation Review Technique (PERT) for time estimates. Then, we follow with a Management Science teaching approach using PERT simulations and cost estimates. For both approaches we discuss their associated risks. In the next section, we present AI basics and its applicability to PM along with its advantages. We include a separate section to introduce AI methods for PM using IBM’s Watson AI platform. In this first phase of research, our goal is to fully present the limitations of teaching PM with predictions based on time estimates and propose an explainable AI teaching approach. Finally, the conclusion section covers future research work.

**Current Teaching Curriculum, PMBOK Process, and Tools**

The most common current PM teaching curriculum includes all the well-known and standard techniques for estimation (e.g., Top-Down, Parametric, Three-Point) to execution to closing. The standard method that is most popular today is the Project Management Book of Knowledge (PMBOK; first published in 1996) process and the use of computer-aided PM tools (e.g., MS Project, Jira, SmartSheet, etc.). This set of tools have been around for at least a generation. For project managers, getting and maintaining a PMI certification is considered key to their professional standing. All tools for estimation, budgeting (cost), scheduling (time), and project tracking are well built into these PM processes and computer-aided tools. The technology used in the PM curriculum and professional practice has not changed much in a generation. The PMBOK process is based on a linear model and the feedback to take corrective action is mostly in the execution phase. Business school Management Science also teaches PM estimations using software simulations.
The above-mentioned process and tools have been working well so far for PM. Today’s project sizes vary from small (3-6 months) duration for mobile apps to a large military project which can go on for many years. The only recognizable change in the process that has come about in many years is the introduction of Agile methodology which focuses on smaller development cycles (iterations of 2-4 weeks each in most cases) to meet the customer needs in a strong team. Agile mostly uses spreadsheet type tools for tracking various project elements. The data created for the huge volume of projects completed with the computer-aided tools are forgotten after a postmortem of a project and some lessons learned that might be used within an enterprise for the next project.

Historical project data is very significant in today’s data analysis. PM education and training are yet to fully embrace the use of historical data and data analysis techniques. PM function is ready to jump to the next level with historical data analysis and the jump can be significant with the use of AI technology. A brief AI introduction and its use in PM will be discussed in the next sections. Both educators and professional institutions like PMI have recognized the importance and potential of AI and its adoption to PM.

**Artificial Intelligence – Basics and Its Applicability to Project Management**

“AI is typically defined as the ability of a machine to perform cognitive functions we associate with human minds, such as perceiving, reasoning, learning, and problem-solving. Examples of technologies that enable AI to solve business problems are robotics and autonomous vehicles, computer vision, language, virtual agents, and machine learning” [1]. Further, historical data on a large set of similar projects is the foundation for AI and machine learning [2] AI technology and its associated data analysis can learn from past historical data by recognizing patterns and it can adjust to new inputs for a better output prediction. AI technology’s self-learning through algorithms is referred to as Machine Learning (ML) and Deep Learning (DL). Figure 1 shows how the two self-learning techniques are encapsulated within AI technology implementation, as described by IBM. With the help of hi-powered computers, these algorithmic self-training technologies can process large amounts of data and recognize patterns. Adoption of these will result in a new set of Tools Techniques and Procedures (TTP)s for better PM performance well beyond what is currently being used.

![Figure 1. AI and its Encapsulated Self-Learning Methods](image)
Well known and widely used implementation of AI is IBM’s Watson, Apple’s Siri, and Google’s Assistant. AI technology implementation is spreading wide and fast into many other areas such as health care, manufacturing, electric utilities, retail, and education [3]. The focus of this research paper is to investigate and validate what features of PM can be enhanced with the adoption of AI and proposal to fold them into the PM curriculum. Once the PM curriculum recognizes and demonstrates the advantages of AI, one can expect that PM field professionals will embrace it as well.

In today’s PM processes and execution, the Project Manager’s knowledge, professionalism, and most of all experience is key to the success of a project. Not all project managers are made equal and one’s experience might have different project outcomes. In the AI world, the experience is reflected in the data that is collected and provided to algorithms to come up with an instant prediction of any of the elements of a project such as a schedule/time or cost. The concept of prediction based on past historical data analysis is not common in today’s PM. Literature review shows several papers written on the advantages of using AI for PM. The construction industry notes that AI is the next frontier and will help overcome the industry’s greatest challenges including cost and schedule overruns [4]. Montgomery [5] identifies five very specific advantages of AI for PM:

- Automate repetitive and tedious tasks
- Use historical data to perform calculations and predictions to improve the accuracy of results.
- Perform risk modeling based on a change of scope, resources, budget
- Increase speed of decision making
- Optimize resource scheduling and allocation.

AI is referred to as being a game-changer for PM in helping to accelerate productivity and increase project success rates [6] In an extreme but realistic expectation from AI, Gartner predicts PM Bots equipped with speech or text interfaces for communication with humans providing instant responses for inquires [7], [8].

In this research, two project elements, namely Schedule/Time and Cost will be explored with their impacts on risk with the application of AI Tools, Techniques, and Procedures (TTRs).

**Project Management Framework : Current and AI-Adopted Processes**

This section will cover the PMI’s professional framework and its application in higher education. It will also cover how AI system or platform will interface with PMI’s framework.

The most common PM teaching curriculum follows the Project Management Book of Knowledge [9] methodology. Several well-known PM textbooks [10] used in higher education and PMI’s professional certification are based on PMBOK methodology. Figure 2 shows the overview of how PMBOK models its process groups and the knowledge areas, and their interactions.
The general approach here is linear phased approach starting with initiation and ending with project closing, for a total of five process groups covering ten knowledge areas. The knowledge areas are the project elements to be managed by a project manager. The process groups, in general, do not have a feedback loop except during the execution phase. In this model, once planning is completed, the project completion parameters (e.g., schedule/time, cost, financial aspects) are tracked during the execution phase. Any deviation from the plan is being corrected during execution. This may be too late to make corrections or changes to meet the initial planned completion resulting in time delays and cost overruns.

Under this PMBOK’s model, although different knowledge areas are addressed during planning stage, the project is looking to estimate the project parameters such as completion date, risk, total cost, etc. This is now the common PM practice followed both in teaching curriculum and certifications.

The above model does not present an opportunity to look at different possible scenarios with different sets of data for similarly completed projects (i.e., data mining) and to be able to instantly assess and compare the project parameters during the planning stage. One does not have to wait until the project is in the execution phase to see real impacts. The use of AI TTR presents this type of forward-looking opportunity to project managers during the planning phase. This AI

<table>
<thead>
<tr>
<th>PMBOK Process Group</th>
<th>Initiation</th>
<th>Planning</th>
<th>Execution</th>
<th>Monitor and Control</th>
<th>Closing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Integration</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>XXX</td>
</tr>
<tr>
<td>2 Scope</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>3 Schedule/Time</td>
<td>X</td>
<td></td>
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<tr>
<td>4 Cost</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>5 Risk</td>
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<td>X</td>
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<td>6 Quality</td>
<td>X</td>
<td>X</td>
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<td>7 Resource</td>
<td>X</td>
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<td>9 Procurement</td>
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<tr>
<td>10 Stakeholder</td>
<td>X</td>
<td>X</td>
<td>X</td>
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</table>

Figure 2. PMBOK’s Process Group Mapping [9] and Interface to AI
(Note – Black arrows are enquiry into the AI system from project phases).
approach presents opportunities to change project parameters, and instantly re-assess the expected results well before the execution phase.

PM Framework with AI Technology Adoption.

The advantages of adopting AI technology into PM were noted earlier. Figure 2 shows how the AI Prediction System can interface with mainstream PM process groups. AI prediction system generally consists of three major software components: Database, Expert System, and Output processing. For any AI project, the key is the database that is built with information from many similar projects. The Expert System (e.g., IBM’s Watson) is the processing engine and it has all the algorithms built-in which analyze the database for a given inquiry. The output of the data analysis from the Expert system must be displayed to the inquiry requestor (or to a file) and this is the third component of the AI prediction system.

As shown in Figure 2, the PMBOK’s main phases are still important parts of PM and show how project key players (e.g., project manager) enquires work. The AI system (all three components) itself will most likely reside in the cloud. The AI system is self-learning with additional databases and inquiries. This is referred to as machine learning and the algorithms for this are built within the Expert System. This type of interface can be made available during PM teaching and to the professionals. There are existing AI systems (e.g., Watson) whose expert system algorithms can be adapted for PM without the need for each organization to develop its algorithms. This is a big advantage and many companies (e.g., IBM, Google, AWS) is providing free access to their AI systems free of charge to educational institutions with limited access to lite features.

Although a project execution may still be linear (e.g., construction), with an AI interface and the ability to change project parameters with enquires, it makes the process feedback-driven at every stage and at any time. The inquiries could start early during the Initiation phase and continue throughout the life cycle of the project. The AI approach would be most beneficial during the planning phase when all the project parameters can be checked and fine-tuned for better performance and results. This AI-PM interface will be further explained in the next section as to how this research approach demonstrates the AI-PM system and its working using an AI system in the cloud.

PM’s Time Predictability and Artificial Intelligence:

Current Approach for Time Estimation Prediction

One of the first challenges faced by any project manager is the responsibility of scheduling a project with all its identified tasks and their dependencies (e.g., predecessors). Highly developed analytical scheduling techniques have been developed and in use now by many standard tools. One important method used in scheduling is the PERT technique (Program Evaluation and Review Technique) which uses probabilistic activity time estimates of all tasks in a project. PERT uses the flexible beta distribution technique (as opposed to a normal distribution) for the three levels of estimation for each task which is generally asymmetrical. The three levels of estimation for each task are noted as follows: optimistic time estimate (‘a’), pessimistic time estimate (‘b’), and the most likely time estimate or mode (‘m’). The project is addressing to
minimize the risk associated with each task completion with three estimates and estimates the best possible completion time using beta distribution. See Table 1 for a typical representative project with 15 different tasks and the table shows all the three estimates for each task.

Standard statistical beta distribution formulae are used to calculate the average expected time to complete each of the tasks (te) given the three estimates, and thus for the whole project, Te, can also be estimated. Per the beta symmetrical distribution approach, the probability to complete the whole project, Te, is 50% (i.e., statistical Z=0). This also means that the risk here is a 50% probability of failure. From Table 1, the project can be expected to complete in 88.5 units of time with a 50% probability for its critical path. This is just a starting point in this method and no PM will be presenting a project to upper management at this 50% level of success (or failure).

Projects need a much higher probability rate of completion and this initial set of calculations form the basis for further exploration on the various probabilities of project completion (e.g., 80% - 90% or better) with Z values greater than 1.

Table -1 Project A - PERT Calculations

<table>
<thead>
<tr>
<th>Project Tasks (15)</th>
<th>a</th>
<th>b</th>
<th>Optimistic time</th>
<th>Most Likely time</th>
<th>Most Pessimistic time</th>
<th>Predecessor Activities</th>
<th>Expected Duration to complete (te/Te)</th>
<th>Variance (σ²)</th>
<th>Std Deviation (σ)</th>
<th>Total Project Duration D days</th>
<th>Probability from NORMDIST function</th>
<th>% Probability to Complete</th>
<th>% Risk associated to Fail</th>
<th>Actual Days</th>
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<td>4</td>
<td>6</td>
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<td>88.50</td>
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<td>90.50</td>
<td>0.68</td>
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<td>68%</td>
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<td>1.00</td>
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<td>0%</td>
<td>8.5</td>
</tr>
</tbody>
</table>

Critical Path is = 1-3-5-7-8 TO 15; Project Te for Critical Path (µ) = 115.5

Note that all these calculations and derivations are based on human-derived mathematical equations, rules for prediction and it applies to just this and only this project. A project manager needs to calculate the expected duration given a probability completion or calculate the probability given a completion duration time. The manager has to redo all the calculations for another project since this is valid for one given project only. The project manager plays a big role in this approach, generally with manual intervention. Most project management education today reflects this teaching approach for time estimations.

The information in Table 1 used all the standard beta distribution calculations formulae including Z and probabilities calculations. It is also important to note for this project A, from Table 1 the...
Te was 88.5 days and in Table 1, as expected, the completion probability at 88.5 time-units (days) is at 50% (this confirms the calculations to be correct) and for 100% probability to complete the project (row 15), the total time it would take will be the sum of actuals for each task and this 115.50 units of time as shown in Table 1.

With the completion probability for a desired duration of the project, it also gives the risk in that duration as shown in Table 1. The actual total time being greater than what the calculations show is not uncommon in projects whether they are construction or software or other. This is reality. This knowledge gained in this project pretty much stays within this project and does not help in a way to predict the next similar project except providing clues and interest in similar tasks. This is where AI will make a difference as described in the next section.

AI’s Approach for Time Estimation Prediction

The data for this project from Table 1 will be entered in the AI database as a flat-file – all tasks(te) and the project (Te) total actual units of time. For AI large amount of such project, data is key for analysis and more accurate output. For this research as noted in earlier sections, a large AI database with similar data was created with over six hundred projects to reflect real-world data for this research and was deployed into Watson.

Once the database is accepted into Watson, the project manager now is ready to input a new project tasks data, and Watson will output the expected actual duration for the new project within a short time (in 10s of seconds). This is asking Watson AI the question - ‘For the given set of tasks for a project, what is the predicted expected time duration to complete the project?’.

Watson AI algorithm also outputs ‘influencers’ – shows the task(s) that most influence the output. This is really ‘risk’ identification and the practitioners now can look at the specific task(s) identified by AI and start mitigation plans early in the project cycle.

This was done successfully for this research project with many project inputs. In addition to the estimated time duration output to complete a given new project, this research verified the following attributes of AI (as noted in the Introduction):

- Faster speed to calculate the estimated actual completion, as noted above. This is orders of magnitude shorter than a practitioner might be able to do with spreadsheet software and applies only to one project.
- To verify that the model can be trusted, one of the project data already in the AI database was input as a new project and AI Watson’s estimated actual completion output was 99.9% of the value of the actual value entered in the database. This also reflects the accuracy of the output of AI.
- The algorithmic pipeline also suggests ‘influencers’ on the project – which tasks and their relationships can potentially pose a problem. This is not possible in a spreadsheet type of estimation. These are risks and PM can develop a mitigation plan.
- The above attributes of AI make it easy to explain the output to management and PM practitioners the AI technology and its output.
PM needs to move forward to bring AI teaching methodologies into higher learning and these steps will be covered in later sections in this paper.

PM’s Cost/Economic Predictability and Artificial Intelligence

In the area of management science in Business Schools, time scheduling and cost management have benefited from the introduction of simulation tools and appropriate algorithms that are readily available for Excel, the most common spreadsheet for business and education. Simulations enhance the traditional PERT analysis of scheduling activities and cost reduction strategies \[11\] – \[13\] In this section, we present some of these improvements appropriate for classroom settings and we start by recalling the critical path found in the previous section includes twelve tasks, T1, T3, T5, T6 – T15, and the expected project completion time is 88.5 days.

These findings depend on assuming task times are measured by their mean given that task times are uncertain within a range determined by the optimistic, most likely, and pessimistic values. Using the mean as an estimation of uncertain task times is useful and relatively easy to implement in Excel, as we have seen before. However, the PERT model becomes deterministic and may give an optimistic outcome because of the flaw of averages \[13\]. To overcome this limitation, we can build a PERT simulation model that explicitly use random task times from triangular distributions that consider the optimistic, most likely, and pessimistic parameters for each task, calculate the estimated project completion time for each set of random task times, run the simulation up to 1000 iterations, and provide a summary of all those results.

Simulations can be implemented in Excel by installing add-ins. In this paper, we use the add-in @RISK that is freely available for educational purposes.\(^1\) The simulation runs the model 1,000 times and provides the complete density distribution of completion times as shown in Figure 4. The mean is 88.76 days, larger than the 88.5 found under the deterministic model based on average task times. That model was slightly optimistic by ignoring the chances tasks could be over their respective means. The minimum and maximum project estimated completion times are 75.5 and 103.5 days, respectively.

The distribution in Figure 3 (left side) illustrates how risky the project is. There is a 50% probability the project could be finalized in 88.7 days, but because the distribution is skewed to the right of the mean, the probability the project could be finished in 92 days is 75%, and that it could be finished in 85 days is just 20.38%. Simulation models can help project managers to design strategies to reduce risk or improve the probability that the project could be finished in 88 unit times or earlier by focusing on the tasks that influence the project completion time the most.

One important difference between deterministic and simulation models is that tasks in PERT simulation models have probabilities of being on the critical path. So, not all 12 critical tasks identified in the deterministic PERT model will be on that path with a 100% probability. For

\(^1\) There are many add-ins for Excel to do simulations for risk analysis. We use in this paper @RISK because Palisade provides an educational free subscription for a year incorporated in Winston/Albright’s Practical Management Science, 6e, Cengage textbook. There are many other textbooks that also includes free @RISK subscriptions.
instance, we found T3 has a 50.6% probability of being on it and T12 has a 100% chance. More importantly, we can use variance influence, correlation coefficients, and regression coefficients to identify the tasks that are most influential on the project completion time. Figure 3 (right side) shows the ranking of influence based on regression coefficients, and the most influential tasks are T12, T7, T1, T3, and T5.2

Knowing that only five out of fifteen tasks are the most influential on the outcome is very useful for project managers interested in crashing tasks to reduce the risk of completing the project on time. Assuming all costs are the same for all tasks, the limited resources available to the firm can now be allocated in just these few critical tasks, for instance, T1 and T12. These two tasks have triangular distributions with parameters (4, 6, 13) and (3, 8, 12). If the managers invest resources in expertise, training, or getting more experienced workers for these two tasks, their maximum values could be reduced and their most likely values could be moved slightly to the left. The resulting distributions could be skewed to the left rather than to the right and end up with a distribution that looks like the one for T7 that has (3, 6, 11) parameters.

Figure 3 – PERT Simulation Project Completion Time and Task Regression Coefficients

If T1 and T12 have distributions based on min, most likely, and max values (3, 6, 11), and nothing else changes in the simulation model, the risk can be shown to reduce considerably.

As we mentioned before, the crash time methodology is useful for projects where the costs of reducing time in all tasks are the same. However, most of the time projects have different costs per task. The following simulation model inserts two cost variables: the cost per day per task and the maximum crash amount per task (Figure 4).

For instance, the cost of crashing T1 and T12 are $600 and $423 per day, respectively, and their maximum reductions are three days. If we apply these max reductions, then the duration of these tasks after the crash would be 3.83 and 4.83, and all other tasks would last the time given by their implied means (green column in Figure 7). Using this 'duration after crash times’ in the PERT methodology, the project would be finished in 82.5 days and the cost of crashing would be

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2 These same five tasks, T12, T7, T1, T3 and T5 also appear as the most influential for variance contribution and correlation coefficients.
$3,069. Given that we already know T1 and T2 were very influential tasks, crashing them to the max seems to be a good start to find out if other crashing time combinations would be done with a cost lower than $3,069.

The simulation model we propose for classroom use is a customized version from Winston and Albright’s crashing model [13]. The simulation model is set to find the crash amounts per task that minimize the cost of crashing up to a determined deadline, for instance, 85 days. The add-in we use to run this simulation is Solver, an add-in incorporated in Excel that just needs to be activated in the Menu Excel options for Add-ins. We run 10,000 iterations, and we have two algorithms to generate the set of crash amounts and find the answer, genetic algorithm (evolutionary method) and generalized reduced gradient (GRG nonlinear method). The evolutionary method found a minimum crashing cost of $1,389.81 and the GRC nonlinear improved this result down to $1260. This minimum cost is achieved if tasks T8 and T10 are reduced in 0.83 and 2.67 days using non-linear algorithm.

<table>
<thead>
<tr>
<th>Project Tasks</th>
<th>Parameters for PERT distributions</th>
<th>Crashing Section</th>
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<tr>
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<td>T2</td>
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<td>T5,T6</td>
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<td>T3</td>
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<td>T6,T14</td>
<td>Finish</td>
</tr>
</tbody>
</table>

**Figure 4 – Crash PERT model with different costs per task**

**Limitations of Simulations for PERT analysis and AI potential**

In terms of algorithms to generate random values, most students are familiar with the Monte Carlo algorithm. However, here we used a Latin Hypercube algorithm because it appears to be more accurate than Monte Carlo for sampling and it is an option included in @Risk [13] – [15].

Finally, we have chosen tasks T1 and T12 as the most influential out of five tasks and suggested making their distributions like the one for T7. This suggestion reduced the risk of completing the project on time considerably, but it was an ad-hoc choice to illustrate a point within a classroom setting.

Simulations for PERT crashing cost analysis depend on the algorithm that supports the solution method. Genetic algorithms generate new samples following rules for permutations and mutations to find max/min values, are relatively fast, and will always find a solution for non-
linear problems. This result is usually improved by the GRG algorithm that is based on finding slope values until it reaches zero to signal a max/min in convex/concave sections of the objective function. Allowing GRG for multiple starting points allows the method to overcome local max/min solutions instead of global answers. However, the results are always very close to the best outcome, and it may be a better result if the non-linear problem could be converted into a linear problem and solved with Simplex [13]. In other words, non-linear simulations to reduce costs are very good and useful, but we should always consider that after combining genetic and GRG methods, it may be a marginal improvement still available.

We will see in the next section how AI can overcome these limitations with its different approach to PERT. The results will not depend on what distribution we select for tasks, what specific algorithm we use to generate random values, what algorithms support non-linear optimization models, or what would be our initial values.

**Methodology for Educational Artificial Intelligence In PM**

The purpose of this paper is to demonstrate the first phase of Educational Artificial Intelligence (AI) applied to project management (PM) through simulation, AutoAI, and Explainable AI (XAI). To demonstrate this initial relationship, the students will have the opportunity to build traditional models to explain a project with its time and cost parameters for value creation, and simply see that artificial intelligence using IBM Watson can come up with the same models that they use for prediction [16]. Constructing a curriculum around traditional algorithm development as well as simulation provides a doorway of explanation as well as trust in artificial intelligence, auto AI, and XAI. The traditional curriculum shows the relationship in this case between time and costs through Program Evaluation and Review Technique (PERT) analysis. This type of Data-Driven prediction is based on an algorithmic or programmatic approach that uses existing models in a series of steps allowing for input to be processed and outputs to be formed [17]. Conversely, artificial intelligence and machine learning take the approach of inputting large datasets for which algorithms and estimations rule sets can be devised, expanded, and augmented [18]. As shown in Figure 6, by allowing students to see the comparison between traditional simulation models and machine learning models, the students begin to uncover the procedures and methods utilized in artificial intelligence that build these effective models for prediction and lead towards XAI.

In terms of curriculum, the course begins with examples of traditional simulation and prediction using statistical models in Excel coupled with iterations using these simulation functions. Next, the course allows students recognize variations between predictions based on estimations (tasks and total project) and a simulation of actual outcomes.
The distinction between estimates and actuals makes students realize that although the models and algorithms have predictive value, the accuracy of the model will always be in question since real-world outcomes will often differ at least slightly. This raises the question of whether better models can be generated as well as improved on existing models to better fit the context of the project or the specifics of other elements, such as environment, leadership, or client. Traditional models and algorithms can be adjusted for specific circumstances but are often more generally applied and taught. This is where artificial intelligence and machine learning show their benefit through using historical datasets to best determine patterns and algorithms, features and convolutions, that best-fit circumstance from actual data that has been realized in actual projects [19].

The following five-step proposal can successfully introduce AI in PM teaching.

**Step 1: Demonstrating Traditional Models and Estimation through Algorithms and Simulation:**

By using traditional PERT equations, estimation techniques for project management, and simulation, the students begin to practice and understand the power of using programmatic and iterative pathways to create datasets that represent possible outcomes within the project. As it was shown in Table 1 before, this type of programmatic approach shows that the body of knowledge, as well as the students' insights, can allow for a general estimation of project outcomes in terms of time and cost. However, students will realize that there is a consistent variation between estimated times and costs when compared to real data of actual projects. Although this may seem obvious, or even acceptable, it certainly begs the question of whether a better model or algorithm can be developed to explain the relationship between estimation and real-world outcomes. This is where theoretical and generalized models show their weaknesses and allow for an opportunity for technologies that can better fit and realize more accurate predictions than the simulation [17].

**Step 2: Preparing a Dataset for IBM Watson Cloud**

To demonstrate that the programmatic solution derived from traditional algorithms and simulation is achievable through artificial intelligence, the students will prepare their datasets for task estimation and estimated outcomes. This type of reverse engineering shows the student that
although equations for pert have been applied to derive the data, machine learning through IBM Watson AutoAI is capable of interpolating and extrapolating their same outcomes, based on an automated algorithm and feature convolution. This also provides the opportunity for students to examine the constituent elements that create the auto AI algorithm, feature, and optimization selections that lead towards a model that best matches their work through equations and simulation while providing the transparency of XAI.

This framework for teaching the use of AutoAI to build towards XAI in project management allows for trust and understanding of the system to take place and may inform regulation and policy around a project. Figure 6 shows the original PERT project from Excel built on traditional estimation through programmatic solution and consumed in IBM Cloud with data refinement, where auto datatypes are assigned. Once the traditional PERT models are built the students transition to using IBM Watson to visualize and understand the benefit and procedures for implementing AI into the project.

![Table](image)

**Figure 6: Create, Upload, and Refine Data in IBM Cloud**

In contrast to traditional PERT, AI algorithms and models provide insights into business decisions that allow for concentration on specific attributes or features that may yield further optimization or performance results [21]. Machine learning algorithms coupled with data analytics models allow processes to be examined at the constituent or base levels of systems or subsystems while examining the context by which these key elements or metrics are influenced or optimized. Traditional AI requires that attributes be fully defined and specific selections of attributes, algorithms, and convolutions or manipulations selected. Additionally, data type or formatting needs to be defined in advance to appropriately manipulate or work with values [22]. Additionally, algorithm testing is required in a traditional method to begin testing on specific algorithms that may perform better on a particular task or decision process. The bridge to XAI or AutoAI allows these decision structures and frameworks to be a programmatic process that allows for rapid interrogation of data, algorithms, and models that can be employed in a machine learning solution. Figure 6 shows the transition from training the AI model and moving towards predictions from that model, which is explored in the next step.

**Step 3: Initialize AutoAI in IBM Watson Cloud**
Using a Watson Machine Learning service, through AutoAI, a compute plan can be established that chooses a machine learning pathway as well as compute resources. Datasets can be allocated to the compute plan. In the foundation for the AI solution is now in place to begin the AutoAI and Explainable AI (XAI) process [23]. Next, the AutoAI process well provides the columns of the data set with predetermined or best fit data types in place. From this selection, it becomes easier for the user to select a prediction column that can be of these generic data types such as integer, string, or decimal. Based on the prediction columns data type, AutoAI will then narrow the algorithm selections types or prediction type to match possible values or outcomes within that data type. For example, a column may evolve string data that is binary, therefore a prediction type of binary classification would be chosen, and this would narrow the possible search of algorithms to fit this prediction process.

Now a user can further define the experiment values by examining the prediction column, column data type, data source, and defining the training data split. The training data split sets the amount of the original data set for which to build the AI models the percentage remaining to test the models that are developed. For example, training data split of 90% with holdout data split of 10% instructs the AutoAI to use 90% of the given data set to build or find the appropriate models and filters and use the holdout data the 10% to test the models for their various predict ‘if’ capabilities. This step in the AutoAI experiment also allows the user to select important columns within the data set that can be used within the algorithm and filter experiment and selection process, this opportunity affords the user the potential to disregard or exclude columns such as key identification or irrelevant columns within the data set. In Figure 7 students can visualize the Pipeline pathways through the relationship map and begins to demonstrate the various factors used to select an optimized model.

**Step 4: Moving towards Explainable AI (XAI)**

Within the AutoAI, experiment prediction settings allow the user to focus on possible prediction types such as binary classification, multi-class classification, and regression. The binary classification will classify data into two distinct categories within the column, where multiclass classification allows for multiple distinct categories, and finally, regression allows for a continuous set of values along with a large range of possible outcomes [23]. Within this section of the experiment settings, the user can choose the optimization metric for which the test across multiple algorithms will be initially judged and reported. The metric output includes ROCAUC, accuracy, average precision, precision, recall, F1, and log loss. The user can also choose to include or exclude algorithms for the experiment [24], [21], including binary classification, decision tree classifier, extra trees classifier, gradient boosting classifier, LGBM classifier, logistic regression, random forest classifier, and XGB classifier.
Figure 7: Graphic Representation of AutoAI Estimator Selection and Pipelines for XAI

Working with regression would add two additional models, linear regression and ridge regression. The general experiment settings include the number of iterations and depth of iterations that will be performed, such as branching factors, initial model tuning iterations, feature engineering iterations, and final model tuning iterations. Figure 8 shows the evaluation measures selected to rank possible models and allows the student to compare the models independently and collectively. Now the user can run the experiment which begins with splitting the data, preprocesses the data, and proceeds to the model selection iterative process and testing steps.

Figure 8: AutoAI Pipeline Ranking Criteria and Metrics

Utilizing the progress map and pipeline generation, algorithm selection as well as feature gendering, and Hyperparameter Optimization allow for multiple comparable vectors towards the AutoAI solution. This comparative process is sometimes known as Dataset Model tuning comes
out where parameters, features, and algorithms are compared and combined to create multiple model paths. In the AutoAI process, multiple model paths are generated based on the criteria in the experiment settings and the next phases of the process allow an in-depth analysis of pattern and model selection to move towards explainable AI (XAI). In the IBM Watson user interface, data is represented for each path, starting with the data set and experiment parameters, top-level algorithms, pipeline vectors, and feature Transformers [21].

![Feature Transformations]

Figure 9: AutoAI Feature Transformation shows the Fine-Tuning of the Pipeline.

The training data as well as folds and holdouts are part of the experiment settings and can be reconfigured to better suit the data structure and size. Moving towards Explainable AI (XAI), each pipeline can be investigated in greater detail through the general interface or in a subsystem that identifies granular information for the model creation. Evaluation detail includes model evaluation, confusion matrix, and the precision-recall curve. Additionally, moving towards XAI pathways requires the model information as well as overarching feature importance. This tells the end-user what patterns have been recognized and have the greatest inputs towards reaching AI predictive decisions. Once a primary or starting model is selected it can be saved in the project asset list as a Watson Machine Learning (WML) or moved into a notebook (a scripted view of algorithms and Transformers) for further investigation and utilization. At this point, models can be published to a catalog or deployed for application development or testing. Figures 9 and 10 show the AutoAI output for Feature Transformation and Importance in a model and allows the students to test project variables for consistency with assumptions such as a critical path or cost analysis. These same figures can also be interpreted as how AI sees the risk in the individual tasks and their combination – an important output for a project manager to mitigate. Seeing the match between traditional assumptions and AutoAI importance builds trust and transparency in the AutoAI and makes it explainable to stakeholders.
Step 5, Building Trust by Testing XAI vs. Traditional Simulation

In the IBM Watson studio, deployment is facilitated by web service and access can be granted via programming code examples as well as a testing interface that provides a web form for input as well as acceptance of JSON files for batch testing. Utilizing Auto AI for this deployment provides a method for auto-scoring of predictive outcomes. In the Watson studio interface, once deployment has been generated, this web service gives information on the overall model and elements that founded its creation, and implementation area that provides programming snippets in cURL, Java, JavaScript, Python, and Scala, and finally the testing interface where inputs can be tested directly against the model. In Figure 11, the student can test the models with a web form or JSON interface allowing for immediate confirmation of model predictive capabilities and helps determine congruency with traditional models. This prediction output allows students to compare IBM Watson AutoAI to the traditional simulation performed in the PM courses. The ability for AutoAI to reverse engineer or reveal the output traditional equations and simulation confirms to the learner that the AI output is dependable and trustworthy. This is the power and significance of this phase one understanding of educational AI, confirming trust and transparency within the explainable AI (XAI) process.

Challenges of PM-AI Teaching

In the five step process above, it was also shown how the students can learn both the programmatic and AI approaches initially so they can compare. In the current state with the lack of available open-access information to immediately switch to this approach would pose some challenges. Most importantly the lack of availability of large number of open-access project databases and the algorithms to run them are obstacles. Project management students who do not have strong computer science would need help to use both these tools. The other challenge
would be companies not willing to share all their project specific databases to be available in an open-access environment.

![API reference](image.jpg)

**Figure 11: Testing and Prediction Interface in IBM Watson**

Project Management Institute (PMI) has already recognized the importance of this approach and it can play a big part in becoming a project database warehouse, voluntarily submitted by many organizations. With a strong initiative, this database can quickly grow and can be made available to educational institutions and PM professionals. This could also be done with Federal Government grants to create central project databases (similar open access databases by Federal government now available for sustainable energy buildings). Access to the use of algorithms can also pose a challenge. This might come a little easier with many companies currently developing many general AI algorithms, will move to share them with educational institutions. IBM has shown strong interest to share the use of their AI tool Watson with educational institutions. In the meantime, it is important to make PM students aware of this upcoming technology through research papers like this. These steps would go a long way to help alleviate the obstacles for teaching PM-AI. Over time with the availability of open-access project databases and algorithms, educational institutions can switch to teaching PM-AI.

**Conclusion and Recommendations**

The objective of this research paper and educational AI method is to introduce the first phase integration of AI in engineering disciplines and manifests with a threefold approach. First, to explore the application of educational AI, through a modern XAI interface for project
management courses. Second, to identify the current methods of teaching PM as it relates to time and cost estimates with the PERT approach. Third, to bring in the application of new AI technology for PM estimations, demonstrate its use with the Watson platform and how this approach can be introduced to teach PM. Several advantages of using AI for PM were discussed and demonstrated.

The PERT estimation is discussed with two current teaching methods, (a) the engineering deterministic approach and (b) the Management Science simulation approach which also covered cost. Both approaches addressed risk and allow students to simultaneously learn traditional PM concepts and draw from AI to realize the costs and benefits of each method. A large database reflecting projects time estimation was created to run on the IBM Watson AI platform for new project time prediction. The applicable concepts of ‘trust’ worthiness and ‘Explainable AI’ were described. These are not only significant for today’s upper-level management for accountability and transparency, but also create a bridge to educational AI that can be used to better inform course curriculum and student understanding. The fast response time to a new project time prediction with Watson AI was demonstrated in this research (10s of seconds versus potentially many hours for each iteration). Watson’s Feature transformation and Importance outputs are indicators of risk that a project manager can help mitigate.

Steps to introduce and teach AI for PM in higher education were also described and demonstrated through a comparison of traditional simulation and interpolation through machine learning, auto AI, and deployment of regression models. Initially targeted at graduate students in business and engineering degrees with limited or no statistics and AI background, the educational AI method bridges traditional course content with AI concepts.

The future work expansion and teaching AI concepts and application will be explored in future research and consequent phases of the educational AI process. Founded on XAI, the educational AI process will seek to expand the interpolation and confirmation demonstrated in this research, by showing that existing models can be extrapolated through new values, tasks, and features while building on existing AutoAI models. Future research will include dataset creation and verification for cost and other knowledge areas of PMBOK. Additionally, learners will begin to discover that new PM projects can be evaluated independently and that custom auto AI models can be developed and deployed for prediction. Furthermore, research on how learners can examine entirely unexplored phenomenon and datasets to create, transform, and predict outcomes based on AutoAI provides the bridge from educational experience to professional workplace practicality and practice.

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