By 2025 a significant number of Project Management roles will disappear. Will yours be one of them?[1]

Martin Paver [a2], Dr Stephen Duffield [b]

[a.] CEO/Founder, Projecting Success Ltd, England UK
[b.] Bogangar, New South Wales, Australia

Abstract

Data analytics is beginning to have a significant impact on a number of professions, but project management is a relatively late adopter. This paper outlines the potential impact on specific project management roles, ranging from supplementing current roles through to radically transforming them. We highlight the need for project managers to acquire new advanced digital skills or face the risk of obsolescence as data scientists and analysts provide evidence-based insights tailored to the conditions of the project.

Keywords: Project Management, Risk Management, Project Assurance, Cost & Schedule, Project Planning, Agile, P3M, Python, R, natural language processing, machine learning algorithms, Power BI, Benefits management

---

A statement from a prophet of doom or a realistic vision of the future? In this paper, we make the case that a transformational approach to project, programme and portfolio management will be required in the short to medium term or our profession will wither on the vine. We must adapt.

We have already seen that the introduction of agile method have transformed traditional project management roles and in some instances these roles have disappeared completely. As data science and analytics becomes increasingly accessible, does this pose a new threat to established project management jobs? This paper will examine how these roles are likely to develop over the coming years. Will data scientists and analysts begin to fulfil these new roles or will project managers reskill and adapt?

---

[1] How to cite this paper: Paver, M. and Duffield, S. (2018). By 2025 a significant number of Project Management roles will disappear. Will yours be one of them? *PM World Journal*, Vol. VII, Issue X – October.

[2] *Corresponding author at Projecting Success Ltd, England UK; E-mail address: martinpaver@projectingsuccess.co.uk*

Project Support Officer

Project administration roles typically provide the first step on the ladder for junior project management professionals. If these roles are significantly impacted there is potential to destabilise career progression for talented project managers unless we rethink the overall career path.

Within Table 1 we outline typical roles for a project administrator and how we envisage the potential impact of data science and analytics.

Table 1. Impact of advanced analytics on project support officer roles

Roles	Potential impact of data science and analytics
Tracking and administration of contractual deliverables	• Text analytics can be used to identify when a new deliverable is received. Topic modelling can be used to identify tags and summarise the document, prior to executing a workflow to assign reviewers. • Scripts can be developed to assess compliance against particular standards or contractual requirements and identify omissions. • Machine learning can be used to assess the quality of each section when compared against a body of training material.
Change control log	• Potential for blockchain[3] approach to manage change end to end. Payments are automatically approved when defined conditions are met. • Change requests become increasingly workflowed and automated. • Algorithms check the change management documentation to ensure compliance, accuracy and compliance. • Risks with specific changes are compared against a known dataset of similar changes. Impacts statements are tempered accordingly. • Approvals are automatically crossed checked against centrally held levels of delegated authority.
Forecasting, budgeting,	• Budgets and forecasts can be automatically developed from known benchmarks, amended to take account of the specific attributes of the projects. The role of the project manager will be to explain the rationale for the divergence from the benchmark and what action is being taken to improve delivery performance. • Cost data will be centralised. Tracking variance between forecast and outturn, enabling each project to work to a common set of (tailored) assumptions.

[3] "The blockchain is an incorruptible digital ledger of economic transactions that can be programmed to record not just financial transactions but virtually everything of value." Don & Alex Tapscott, authors Blockchain Revolution (2016)

Roles	Potential impact of data science and analytics
Development of briefs, reports and dashboards,	• Capabilities such as PowerBI or Tableau can already autogenerate textural insights from data, adapting the insights in real time based upon applied filters. • Automatic text summarisation algorithms review documents and summarise the salient points. These algorithms can be tailored to focus on specific areas of concern. • Projects such as the A14, the UK's largest road construction project, are moving away from powerpoint and narrative based reports to interactive business intelligence based on (near) real time data.
Meeting administration, minutes and actions.	• Products such as Microsoft flow can be used to schedule, set up and invite attendees to a meeting, book meeting rooms. Chatbots and virtual assistants are easing the burden. • Voice recognition is already providing transcripts of meetings. • Virtual assistants can capture actions from a meeting and summarise them before the meeting closes. • Workflow automation can be used to track action performance and report Key Performance Indicators (KPIs) via Power BI. • Machine learning can be used to provide an indicator on the quality of the response to the action, identifying when intervention may be required and influencing / advising on a particular course of action.
Project history,	• By identifying key events in the schedule, key meetings in the diary, key documents (e.g. all those sent to the project Sponsor) it is possible to automatically populate the project history. • By using a knowledge graph it is also possible to identify any related documents, decisions or artefacts. • By reviewing the cause and effect of major variance it is also possible to identify key risks, schedule decisions etc which led to the variance and use these documents to inform future decisions.
Monitoring resource utilisation,	• Automatic review of timesheets and comparison of variance against budget. • Recommendations on resource allocation based upon operational priorities but tempered against evidence that illustrates the impact of working below irreducible minimums. • Workflows to progress chase outstanding time sheets. • Enhanced KPIs on areas such as open meeting actions, open risk management actions, frequency of schedule updates, schedule performance vs baseline or benchmark.
Quality reviews,	• Python[4] can be used to identify frequency of updates of documents, the extent of updates and whether they are

[4] Python is a general-purpose programming language. It has a range of native libraries and 3rd-party frameworks to enable developers to perform a range of activities from scraping the content of web sites to cleaning data.

Roles	Potential impact of data science and analytics
	materially significant. Whether key policy documents have been updated. By comparing against a training data set it is also possible to characterise the quality of the narrative.

Within the insurance industry Artificial Intelligence (AI) is already reducing the administrative burden of a number of roles. AI can analyse documents to ensure they have been signed, completed and validated; linking with workflows to ensure that follow up actions are tailored to results. The impact of different campaigns can be measured and adapted in real time to improve participation, the quality of online support and autocompletion of fields. Medical insurance is moving towards automatically approving claims based upon the completeness and accuracy of the claim forms and supporting evidence, combined with comparisons against similar claims for known medical conditions. In the legal profession McKinsey estimate 69% of time is automatable for paralegals and 23% of time is automatable for lawyers.

Project administration roles have the potential to repeat the history of the project typing pool unless they adapt.

Risk Management

There are a range of roles that cover risk management, from the risk expert through to the risk manager. These roles encompass the process of capturing, updating and reporting risk. The risk manager often doesn't manage risk; responsibility sits with the person who is most appropriate to manage the risk. Their role is more of a facilitation role. However, how will this role evolve over the next six years?

Risk Identification

We tend to identify risks by pulling together subject matter experts into a room and brainstorming what these risks are. Chapman (2001) refers to the two principle approaches to risk identification and assessment, as semi-structured interviews conducted with individual design team members in turn and the risk analyst leading a working group. The authors have attended some meetings which are adept at honing in on the risks and issues that are likely to impact the project. However, the authors are also acutely aware that this is subject to bias, groupthink and organisational agendas. At the other end of the spectrum, we have also worked on projects where members of the team perceive risk management as an administrative, form filling exercise that gets in the way of doing their job. It is a mixed bag.

Chapman (2001) also highlights that 'the effectiveness of the identification process will be directly correlated to how broad and comprehensive the examination of the threats to a project are'. Imagine a future where the risk identification is shaped by conducting statistical analysis on projects that have gone before. Rather than producing a crude ranking of probability and impact, we understand the potential consequences from a dataset of historical

projects. Working from a taxonomy and work breakdown structure of risks we can score probability and impact based on hard evidence, tailored to the circumstances of the project. This will change dynamically as the project parameters evolve, learning from the dataset of delivered projects. We have the hard evidence to argue with the sponsors and governance authorities on priorities for investment. We also have evidence of which management actions deliver more success than others, in particular circumstances.

Risk Management

The risk register will auto-update based on the parameters of the project. It has the potential to pick up live feeds from the supply chain through to weather, recommending adjustments to the schedule and risk mitigation investments in real time. Boxarr has a capability to model the complexity of the supply chain and link it to Twitter feeds, capturing risks to the supply chain as conditions develop. Test analytics can analyse the micro narrative from transcripts of project meetings to identify emerging risks such as changes in client personnel, particularly when compared to a known taxonomy of risks. The probability and impact of the risk will be adjusted to the predisposition of the organisation and the project to that risk, derived from the aggregated dataset.

Reporting will become increasingly standardised, automatically identifying whether risk management actions have been completed and executing workflows to chase progress or escalate. Prioritisation of effort will be influenced by the aggregated analysis that illustrates the snowball effect of risks and their contribution to variance.

AI will enable portfolio managers and assurance authorities to assess the variance in approach in risk management strategy across the portfolio, highlighting areas of focus. It will also be able to identify the difference between the aspiration and intent (what was written in the risk management strategy) and reality (what risk activities are actually being performed).

AI provides insights, but we should not rely on it to provide answers. There will always be a need to capture the specific challenges of the project and moderate whatever 'the machine' is telling us. But our immediate challenge is whether these emerging roles are better fulfilled by a risk manager/administrator or a data analyst who can extract insights from the body of evidence that exists?

Risk budgeting

The allocation of contingency and is typically a product of Monte Carlo analysis, with additional management reserve allocated for unknown unknowns.

Flyvbjerg's analysis in 2011 highlighted that 'one in six of the projects we studied was a black swan[5], with a cost overrun of 200%, on average, and a schedule overrun of almost 70%'. Having

[5] Nassim Taleb offers **a definition of a black swan** as 'an event with the following three attributes. First, it is an outlier, as it lies outside the realm of regular expectations, because nothing in the past can convincingly point to its

studied over 20,000 lessons learned we challenge whether these projects are true black swans, i.e. the circumstances that led to the overrun were unknowable. If the organisation doesn't have experience of such a project then it is likely to be unknowable, but if the organisation extends its horizon to all similar projects that have ever been delivered, then the frequency of black swan events should reduce dramatically as the unknown becomes knowable.

Through the forensic analysis of previous projects we have an opportunity to allocate risk budget not just on the basis of Monte Carlo analysis, but also on the outturn of 1000s of similar work packages, adjusted to account for the particular circumstances of a project and its predisposition to failure.

Portfolio managers will have an unprecedented level of insight into risk budgets and reserves across the portfolio.

Scheduling and cost analysis

When we estimate durations for activities, we use expert judgement. People who had done it before and understood the nuances of the business and the process. However, Kahneman and Tversky (1979) identified the tendency of people to underestimate task-completion times and costs even despite the facts that the vast majority of similar tasks have run late or gone over budget.

Estimates can also be subject to optimism bias or entryism, where people strategically misrepresent the true timescales of a project in the belief that they can beat previous schedules. Optimism bias arises from the tendency for people to be over-optimistic by overestimating benefits and underestimating costs (Lovallo and Kahneman, 2003). Strategic misrepresentation occurs on projects where key stakeholders deliberately misrepresent project costs and risks for political, economic, and/or other gains (Flyvbjerg et al., 2006). In order to mitigate optimism bias and strategic misrepresentation, it is necessary to take the "outside view" when developing project plans and making decisions (Kahneman and Lovallo , 1993). This risk management "outside view" involves the intelligent application of past performance data or experience from other projects and from stakeholders who are not investing in the project financially, emotionally or from a career perspective.

Reference Class Forecasting (RCF) provides a methodology to mitigate optimism bias and strategic misrepresentation by applying a dataset of actual performance of comparable past projects within a given reference class to provide an objective reference point for the cost forecast of a current project (Flyvbjerg et al., 2005a). Percentage uplift is determined and added to the base estimate as risk contingency (Flyvbjerg et al., 2002) taking cognisance of the distribution of schedule variance and the project estimators' preference for risk of cost overrun. As the dataset grows, the reference class extends beyond cost and schedule to

possibility. Second, it carries an extreme impact…. Third, in spite of its outlier status, human nature makes us concoct explanations for its occurrence after the fact, making it explainable and predictable'.

capture the key parameters within a deep learning model which could influence schedule out-turn at a work package level. The machine learning takes cognisance of the relevance and applicability of the legacy data, improving the quality of the forecasts as the data develops.

Emerging capabilities from organisations such as nPlan and ALICE help to illustrate the value of aggregating large datasets. They utilise thousands of construction schedules to identify optimised work flows, areas of delivery risk and opportunities to improve delivery efficiency.

There is a broad variance in capability in how costs are estimated, ranging from expert judgement, component level cost databases through to reference class forecasts. They are becoming increasingly sophisticated, blending cost forecasting with the various elements of supporting data, such as that provided via Building Information Modelling (BIM) models. Although component level datasets are commercially available, the knowledge associated with delivering the schedule and estimating the cost of the work breakdown structure tends to reside with the project manager or in house estimating team. However, as organisations begin to pool this data the number of instances of similar projects increases and the reliability in the estimate should also increase. The role of an estimator will evolve from intrinsic knowledge to understanding how statistically relevant cost data is, how to adjust weightings in the model and fine tuning of deep learning models.

As the machine learning capability develops, the system will also flag up early warnings which tend to be a trigger for cost variance, providing recommendations on potential courses of action to mitigate the impact. The system will also have the capability to identify which work packages tend to be predisposed to cost growth.

Reporting

There is a significant variance in the way that project reporting is conducted, ranging from spreadsheets and powerpoint presentations through to real-time interactive PowerBI or Tableau reports. Organisations are increasingly examining the value of integrating their data. The team on the A14, the UK's largest road construction project, have integrated a wide range of data spanning cost, health and safety, productivity, scheduling and a range of other parameters within a series of PowerBI work books. The ability to rapidly extract, clean, transform and load data is becoming a core skill for teams working on advanced reporting. They also need to work closely with information architects, and those responsible for managing cloud services, ranging from apps, storage through to cloud computing. The skills required are rapidly extending beyond Power BI visualisations into PowerPivot, DAX and potentially, R and Python to scrape, clean and align data. As the volume of data grows and the joins become more complex, the benefits of migrating data to graph databases also grow, which brings a new set of challenges with languages such as Cypher.

As the proliferation of dashboards grows, governance authorities and project teams may struggle to see the wood for the trees. The incident at 3 Mile Island illustrates the impact of poorly designed human machine interfaces and dashboards. 'The operators were unable to

diagnose or respond properly to the unplanned automatic shutdown of the reactor. Deficient control room instrumentation and inadequate emergency response training proved to be root causes of the accident'.

There will be a need to draw attention to specific parameters which extend beyond tolerances, with the bounds of those tolerances being established as a product of a statistical analysis of legacy data. Specific types of projects will be predisposed to different conditions at different points in the project lifecycle. Hence the dashboards need to adapt to the factors that are most pertinent at any point in time. Machine learning will also enable the project team to transform analysis into insight, providing recommendations on specific courses of action.

Reporting will also increasingly extend into benchmarking, with live streams of KPIs at WBS level, risks, key stakeholders etc. Tools such as Anaplan provide insights into the capabilities of a platform approach to connecting data, people and plans, providing statistics on individual performance. Statistics and KPIs on individual members of the team will proliferate, identifying risk management actions completed on time, estimating accuracy, stakeholder management feedback; the insights on personal and team performance will begin to multiply.

Assurance

Project assurance comprises 2 main themes:

1. Ensuring adherence to process.
2. Using experience and wisdom to identify and pre-empt potential issues.

In our experience, generally, the more junior assurers tend towards a process-focused approach and the more senior staff coach and guide.

Process Assurance

A significant amount of effort is invested in ensuring that project teams comply with the process. Is the risk register up to date, is the stakeholder management plan complete, is the schedule compliant with DCMA good practice. All of this can be verified using a machine. Data science can then be applied to characterising the quality of the artefacts, comparing them against a training data set. The next step would be to identify the correlation between process maturity and project performance and using it to predict where issues are likely to emerge and prioritise assurance interventions; essentially a risk-based approach to assurance.

In an ideal world, the project should develop a set of artefacts that align with established good practice and bodies of knowledge, tailored to the demands of your project. In reality, resources ebb and flow; you lose your risk manager for a few months and updates degrade. Some of these could crucify your project; others can be tolerated. Tailoring is linked to the experience of your team, but in reality, the dataset of experience provides insights into the relationship between artefacts and project delivery performance. Data science and analytics can help to

understand the extent to which risks are being updated on a monthly basis and also look for specific themes in the narrative. It can also explore correlations between risks, issues, schedule, cost and lessons learned to understand the extent to which they are integrated and aligned.

Maturity Assessment

There are a wide range of assessments that assess the maturity of project, programme and portfolio management capabilities. From P3M3, OPM3, Praxis capability checklists through to the Office Government Commerce Gateway Process, Infrastructure Project Authority's 7 lenses of transformation healthcheck and guidance for reviewers. The latter provides a summary of areas to probe and the evidence that is expected against each line item.

There is a tension between a maturity model based approach, where an organisation aspires to achieve a defined level of maturity by a target data and a checklist approach that requires teams to engage in constructive dialogue. The report Critical Assessment of P3M3 in Australian Federal Government Agencies in 2011 noted a lack of evidence that using P3M3 leads to the claimed benefits. In a recent blog, a P3M3 reviewer commented that "It is widely reported that the average organisation's P3M3 maturity is around level-1.5 on P3M3's five-point scale and that 80% of organisations are at level-2 or below". Despite maturity assessments being in existence for years, there is a lack of consistency in how these tools are applied; their impact isn't sufficiently compelling.

What is clear though is the potential impact that data science could have on characterising P3M capabilities. It has the potential to:

- Offer a decision tree of questions tailored to the type and phase of project, supported by narrative and case studies which are applicable to the specific application.
- Provide an assessment of the likelihood of variance (or exceeding tolerance) based upon the responses to the questions.
- Identify which questions or groups of questions have the greatest impact on performance for a defined set of conditions.
- Tracking whether actions from previous assessments have been completed, then actioning a workflow to trigger follow up events in the event of missed milestones.
- Automatically track performance of specific attributes, such as how frequently risk registers are updated, whether the updates are significant and whether the definition of the risks reflects good practice. This can help to measure capability maturity and process adherence across a range of parameters.
- Advise on the most appropriate course of action and associated priorities.

It provides an evidence-based assessment of maturity to inform discussions and priorities across the enterprise. This could help to transform how maturity assessments are conducted, moving them from being led by independent consultants, to be driven by internal tools and insights, facilitated by third parties. Updates become a by-product of project delivery.

Benefits Management

Benefits management is "the identification, definition, tracking, realisation and optimisation of benefits"(Jenner 2012). In 2017 the UK's Infrastructure and Projects Authority published a Guide for Effective Benefits Management in Major Projects. This guide identifies challenges faced by organisations when adopting and applying benefits management. Table 2 summarises some of these challenges with our perspective on how advanced data analytics may be able to help resolve them:

Table 2. Impact of advanced analytics on benefits management

Challenge	Potential impact of data science and analytics
Project teams and stakeholders are overly optimistic about benefits	• Extract benefits from the original business and compare with achievement. • Understand which benefits were realised, which fell short and understand why. • Improved dataset of evidence to enable more effective scrutiny and assurance.
Benefits management is seen as bureaucratic and time consuming	• Sharing of benefits maps and associated data. Development of knowledge graphs linking strategy, plans and benefits maps. • Auto-population of benefits data using machine learning, tempered with human insights. • Capture correlations between metrics/measures and benefits. • Develop apps, Internet of Things (IoT) or similar to harvest the data to provide better insights into benefits management.
Project is not scoped to deliver the outputs needed to realise the benefits	• Identify the correlation between project scope and benefits realisation using machine learning. Projects of ABC scope have a greater probability of delivering XYZ benefits than DEF scope.
Not engaging with stakeholders enough	• Understand the correlation between stakeholder engagement plans, actual stakeholder engagement, real time feedback on stakeholder perceptions and narrative and how this influences benefits realisation. • Using stakeholder data to understand which stakeholders have had the greatest (+ve or -ve) impact on benefits realisation. • Using data on management actions to understand which ones are the most effective and when is the optimal time to deploy them.
Lack of benefits management data, or poor quality data	• Aggregation and integration of benefits management data. Taxonomies and libraries of benefits management data. • Probabilistic analysis on the likelihood of specific benefits being realised, tailored to the circumstances of the project. • Using data science to assess the quality of the benefits statements and plans (maturity assessment). Identifying frequency of updates and whether they are 'materially significant'. • Using data science to identify correlations between benefits management artefacts and other P3M artefacts (e.g. risk) to identify early warnings.
Not setting aside resource for benefits realisation activities	• Benchmarking resources applied to benefits realisation for different types of projects.

Challenge	Potential impact of data science and analytics
	• Resource profiles vs benefits realisation.
Benefits are difficult to measure	• Identify measures that work for specific benefits and types of projects. Sharing good practice on measures • Auto extraction of data to support benefits realisation analysis. • Using graph technology to aggregate and integrate benefits across different programmes. • Identifying correlations and proxy information to track progress.

Source: Challenges are extracted from Guide for Effective Benefits Management in Major Projects. The remainder of the table is original context by the authors.

Stakeholder Management

The approach to stakeholder management varies significantly across organisations. Some organisations employ stakeholder management professionals to manage relationships across multiple projects, others assign responsibilities to members of the project team. However, if we analyse this data we should be able to understand which stakeholders are closely associated with variance and when this variance is likely to be triggered. What do specific stakeholders require, when do they require it and what are good exemplars. Which sort of approach gets them on board and which sort of approach tends to alienate them?

Some stakeholders may not be aware of the impact of their action, or lack of action. If we are able to connect the data and provide forensic feedback to key stakeholders then we have the opportunity to influence future behaviour. We can also highlight similar cases and the stakeholder's position on them, which should help to control the temptation to change approach.

This analysis can't be captured within a stakeholder management plan. It is dynamic and emergent, evolving based on the conditions of the project and its environment. But the experience that has gone has the potential to significantly ease the burden of this activity and enable projects to run significantly smoother.

Lessons Learned

The need to learn and apply lessons from project delivery is well researched. There is limited research that demonstrates the effectiveness of the lessons learned process (Duffield and Whitty, 2015, Patton, 2001). Instinctively, it is evident that future projects will benefit from leveraging the experience of the past (Burr, 2009, Shergold, 2015). Yet it remains a wicked problem for the P3M profession, where organisational learning from projects rarely happens, and when it does it fails to deliver the intended results (Atkinson et al., 2006, Keegan and Turner, 2001, Kerzner, 2009, Milton, 2010, Schindler and Eppler, 2003, Klakegg et al., 2010, Williams, 2008, Shergold, 2015).

Milton (2010) highlights a significant dissatisfaction with project lessons learned processes. Lessons from projects might be identified, but not many are learned when it comes to picking up on early warning signs in problem projects (Klakegg et al., 2010). Out of 74 organisations that attempted lessons learned processes, 60 percent were dissatisfied (Milton, 2010). In another study, 62 percent of 522 project practitioners responded that they had a process for learning lessons, and of that only 11.7 percent followed the process (Williams, 2007). Furthermore, while the lessons learned process is accessible, it fails to deliver the intended results as lessons are identified and are often not followed through and integrated into the organisation (O'Dell and Hubert, 2011)

Having collated nearly 20,000 lessons learned, the authors have concluded that most organisations are unable to demonstrate that lessons are being learned. The lessons are generally superficial, anodyne and repeat established good practice. In order to extract insights to positively influence project performance, we must look back at what we can extract from the connected data that resides on organisational repositories and SharePoint. For example, did we allow enough time for system testing, did we underestimate the supplier resourcing risk and to what extent? The lessons learned reside in the data rather than a high-level summary that loses context and relevance. The role of the project team will need to evolve from capturing and recording lessons learned to forensically examining the data related to project variance to identify the primary factors, assumptions and decisions that contributed. This requires an accomplished understanding of connected data, how to query that data and to understand the statistical distribution of that data.

The lessons learned log will become a thing of the past, replaced by a connected dataset of experience, discoverable and contextualised to enable professionals to rapidly discover insights and prevent the reinvention of wheels.

Aggregating Data and Data Commons

This article makes the argument that organisations will begin to extract an ever-increasing amount of value from data. But the degree of insight will be constrained by the scope and volume of this data. Organisations who have a pipeline of similar projects will be able to extract more insights than those who conduct infrequent one off projects; the insights come from the patterns in the data. Efficiency and effectiveness will emerge from the aggregation of this data across organisational boundaries through data trusts and data commons.

The 'dig to share' initiative is a good example which seeks to change behaviour in the industry by encouraging organisations to share ground investigation data. Their vision is that all ground investigation data will be shared within a free-to-access central database which could then be accessed by different project stakeholders.

The UK AI review defined a data trust as **a repeatable framework of terms and mechanisms** that 'are not a legal entity or institution, but rather a set of relationships underpinned by a repeatable framework, compliant with parties' obligations'. The 'community-based data

sharing agreements' outlined by the Organisation for Economic Co-operation and Development (OECD) provide a means of improving access to data. It summarises that 'these arrangements are crucial for maximising the value of data by keeping the range of opportunities [for using data] as wide as possible, while limiting the risks of violating the interests of data subjects'. The Kent Integrated Dataset (KID) gathers data from over 200 primary care providers, acute hospitals and mental health services across the UK. It links records from across these services and provides pseudonymised access to the data to inform health and care decisions. The Open Data Institute is also exploring 'ways to increase access to data for new technologies while retaining trust'.

The challenge for project-based organisations will be how to leverage value and insights from this data to improve certainty in delivery and reduce outliers.

The Challenge

This paper has provided a number of insights into how traditional project management roles are likely to evolve over the next 1-5 years. The majority of this capability is already available, it is a matter of adoption and having the quality and range of data to inform the algorithms. The challenge for our profession is how do we engage with it. Will these evolved roles be fulfilled by project managers or is there a need to reskill?

Many organisations will need to wrestle with the decision of whether to be locked into a platform specifically designed for project data analytics or whether they pursue a data-centric approach, integrating data from across their organisation using industry standard tools and cloud services such as PowerBI. How will AI engines be integrated into these capabilities? Who will own the aggregated data that enables the AI? This will require an advanced level of technical competence.

Machine learning will develop recommendations from a black box algorithm which ingests a wide range of data from multiple sources. A key skill for the team will be to understand the parameters that influence algorithm selection, the concepts that underpin the algorithm, its tendency for bias, sensitivity analysis, the impact of weighting, data quality and completeness and a range of other factors. Ultimately, they need to be able to take an informed view on the extent to which they can trust the data.

Conclusion

The majority of the above require knowledge of a range of data science methods ranging from an overview through to expert practitioner.

The rate of progress will be dependent upon organisational information systems, i.e. to what extent are they able to apply new tools and methods. Those who can exploit Python, R, natural language processing, machine learning algorithms, Power BI, graph databases and a range of other systems will progress at a far faster rate than those who are encumbered by legacy

systems and policies. Practitioners will also need to be able to understand the methods by which the analysis and recommendations were produced and assess their validity.

In light of these potential changes, who would you want in your squad to help you to deliver your project? People trained in traditional P3M methods or people trained in data science? Its not a binary decision, but if we do increase the number of analysts, it is likely to be at the expense of traditional roles. Conventional project roles are about to change radically, and the question for our profession is whether that void is filled by upskilling project staff or recruiting a new skillset of data scientists and analysts?

We have a window of opportunity to prepare for and accelerate a transformational future for our profession. If we wait too long, it may be challenging to catch up.

Although this paper paints a stark picture for our profession, it also opens up a whole range of opportunities. AI will enable us to improve project delivery performance and avoid the avoidable. There is also an emerging view that in some sectors AI will create more jobs than it replaces. But these jobs will only be fulfilled by project professionals if we adapt through the acquisition of advanced digital skills and a knowledge of programming; as a minimum, we need to be able to interpret the data that the tools will be providing us with.

References

ATKINSON, R., CRAWFORD, L. & WARD, S. 2006. Fundamental uncertainties in projects and the scope of project management. *International Journal of Project Management,* 24**,** 687-698.

BURR, T. 2009. Helping Government Learn. *In:* COMPTROLLER AND AUDITOR GENERAL, N. A. O. (ed.). London: The Stationary Office.

CHAPMAN, R.J. 2001. The controlling in¯uences on effective risk identification and assessment for construction design management. *International Journal of Project Management,* 19**,** 147-160.

CHRISSIS, M. B., KONRAD, M. & SHRUM, S. 2003. *CMMI® : guidelines for process integration and product improvement,* Boston, Addison-Wesley.

DUFFIELD, S. & WHITTY, S. J. 2015. Developing a systemic lessons learned knowledge model for organisational learning through projects. *International Journal of Project Management,* 33**,** 311-324.

IPA, Guide for Effective Benefits Management in Major Projects, https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/671452/Guide_for_Effective_Benefits_Management_in_Major_Projects.pdf

JENNER, S. 2012. Managing Benefits. APMG International 2012, 15

KEEGAN, A. & TURNER, J. R. 2001. Quantity versus Quality in Project-Based Learning Practices. *Management Learning,* 32**,** 77-98.

KERZNER, H. 2009. *Project management : a systems approach to planning, scheduling, and controlling,* Hoboken, N.J., John Wiley & Sons.

KLAKEGG, O., WILLIAMS, T., WALKER, D., ANDERSEN, B. & MAGNUSSEN, O. 2010. *Early Warning Signs in Complex Projects.,* Newtown Square, Pennsylvania, Project Management Institute Inc.

MILTON, N. 2010. *The Lessons Learned Handbook: Practical Approaches To Learning From Experience,* Oxford, UK, Chandos Publishing.

O'DELL & HUBERT 2011. *The new edge in knowledge : how knowledge management is changing the way we do business,* New Jersey, John Wiley & Sons.

PATTON, M. Q. 2001. Evaluation, knowledge management, best practices, and high quality lessons learned. *American Journal of Evaluation,* 22**,** 329-336.

SCHINDLER, M. & EPPLER, M. J. 2003. Harvesting project knowledge: a review of project learning methods and success factors. *International Journal of Project Management,* 21**,** 219-228.

SHERGOLD, P. 2015. Learning from Failure: Why large government policy initiatives have gone so badly wrong in the past and how the chances of success in the future can be improved. *In:* APSC (ed.). Australian Public Service Commission

WILLIAMS, T. 2007. *Post-Project Reviews to Gain Effective Lessons Learned,* Newtown Square, USA, Project Management Institute.

WILLIAMS, T. 2008. How do organisations learn lessons from projects–and do they? *IEEE Transactions in Engineering Management,* 55**,** 248-266.

About the Authors

Martin Paver

United Kingdom

Martin Paver, Data Scientist, Registered Project Professional, Chartered Engineer, BEng, MBA, MAPM, MIMechE, is CEO of Projecting Success Ltd. and Founder of the London Project Data Analytics meetup.

Martin is a Registered Project Professional with the APM and a Chartered Engineer with the IMechE. He is the CEO/Founder of a P3M and data science consultancy called Projecting Success who help project organisations to connect and understand their data for a more certain, evidence-driven project delivery by analysing historical and real-time data to discover insights and make recommendations with improved confidence in outcomes. He has 30 years of delivery experience spanning senior strategic roles across government and the private sector, led projects of up to $1bn, both client and supply side and he also led a PMO for a $multi-billion portfolio of ICT projects.

In late 2017 Martin established the London Project Data Analytics Meetup, the UK's largest community that combines the cutting edges of data science and project management ranging from hosting talks, delivering hackathons through to influencing future thinking on project data science. He has also been instrumental in establishing a project data analytics work stream within the APM, helping to shine a light on the art of the possible and facilitate the development of a new cadre of professionals.

He is on a mission to leverage the benefits of advanced data science for the benefit of the project management profession, ensuring that we shape the direction of the industry and prepare us for a new future.

Martin can be contacted at martinpaver@projectingsuccess.co.uk

Dr Stephen Duffield, MPM, FAIPM, AFALARA, CPPD

New South Wales, Australia

Stephen Duffield completed a PhD with the University of Southern Queensland and has a research interest in organisational knowledge and lessons learned. Stephen has 38 years' experience with both the public sector (Royal Australian Air Force, Queensland Department of Transport and Main Roads, Queensland Health and the Civil Aviation Safety Authority) and private sector (British Aerospace, AWA and the Boeing Company) organisations with a major focus on program/project management, governance, risk and safety management.

Stephen can be contacted at stephen@invictaprojects.com.au