Managing Data Science Initiatives as Exploratory Projects: A New Approach to Program Management

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Abstract: Despite massive and ever growing investments into data science, it is estimated that 85% of these data science projects do not meet their business aims. This article argues that a big part of the reason is the mis-adaptation of well-established (predictable, exploit-based ICT) program management practices to inherently exploratory and uncertain data science initiatives (DSIs). Informed by a 5-year longitudinal multiple-case study of 7 DSIs delivered at Transport for New South Wales, we explain six distinct properties of DSIs that make traditional delivery and governance practices unsuitable. This study proposes an evidence-based delivery framework that adopts program management, change management, scaled agile, data management and data science practices. Core to this proposal is the notion of "minimum viable governance" (MVG) — a lean, innovative, adaptive governance that provides appropriate level of "control" along with adequate "freedom" for innovation. This findings show the efficacy of managing DSIs as exploratory projects, rather than shoehorning them into existing program structure, in increasing success rates and increasing value realization. Implications for program managers, policymakers, academics are discussed.

***Keywords*:** data science initiatives, exploratory projects, program management, minimum viable governance, agile, scaled agile framework, CRISP-DM

1. Introduction

Data has become a critical strategic asset and organisations across public and private sector invest heavily in Data Science Initiatives (DSIs) to tap into predictive intelligence, optimise processes and enable innovation (Cao, 2017; Mikalef et al., 2018). Unfortunately, the record of these investments is, regrettably, alarming. Industry estimates constantly propose that the failure rate of data science projects is around 85%, more than double that of the industry's usual ICT projects (Mathur, 2024; Shellshear, 2024). A recently conducted study of Shellshear (2024) shows that the actual failure rate for analytically immature organisations is above 90% while analytically mature organisations often experience failure rates in excess of 40%. A systematic review article by Ataei et al. (2024) summarised the results of 26 studies and identified 5 major themes that cause big data project failures: technical factors, organisational factors, ethical and legal concerns, economic factors and methodological factors.

Lahiri and Saltz (2024) did a similar systematic literature review and found that many data science endeavours fail at any project stage and that risks persist after successful adoption of a data science outcome, even in the form of ethical problems, including bias and discrimination. Despite two decades of frameworks and research, these approaches have yet to make a measurable difference to the failure rate (Shellshear, 2024).

Why do so many DSIs fail? This paper argues the answer lies not in the algorithms, but in the management and governance imposed on the DSIs. Traditional program management is not fitted to a DSIs' scope, cost and schedule than constant, and the work flow of data science is exploratory, incremental and highly uncertain (Lenfle, 2024; Atkinson, 1999). A DSI is not a predictable engineering undertaking; it is a discovery-driven venture, in which even the viability of a viable solution may not be known at the outset (Haertel et al., 2024). That's why efforts to force a DSI into a traditional project lifecycle lead to unrealistic business cases, dysfunctional governance and ultimately, project failure.

This study highlights an important gap in the literature for management of DSIs as exploratory projects. Using a longitudinal multiple-case study of 7 DSIs that were delivered over 5 years at Transport for New South Wales (Transport), this paper provides answers to two important issues: first, why conventional practices applied to managing ICT-enabled activities do not produce desired results for DSIs; and second, what design principles should be adopted into a DSI delivery approach that would allow program managers to derive value from DSIs. The study has an interpretivist philosophy and an abductive approach and applies semi-structured interviews, participant observation and archival document analysis across the 7 cases. Our study highlights 6 unique characteristics of DSIs and proposes a comprehensive framework combining program management, change management, scaled agile (SAFe), data management (DAMA-DMBoK), and data science

processes (CRISP-DM).

Central to the framework is the notion of “Minimum Viable Governance” (MVG), or governance that provides just enough control for accountability but not so much as to eliminate innovation (Mathur, 2022). Our paper adds to both theory and practice by proposing a validated, science-based approach to DSIs, and can help organisations increase their chances of success and reap the promised value of data science.

2. Literature Review

2.1 Exploratory versus Exploitative Projects

Understanding the distinction between exploratory projects and exploitative projects is important to understand why DSIs need to be managed differently. For example, Lenfle (2024) classifies exploratory projects as those where both goals and methods to achieve them are not fully determined from the outset. Exploratory projects cannot be managed in a "waterfall-style" approach focused on delivering some work scope, cost and time to completion. Turner and Cochrane (1993) found that "Type-4" projects had both goals and methods unknown at the outset and insisted that they demanded flexible and adaptive management. Contrastingly, exploitative projects involved well-known technologies and requirements that were stable, which allows a project to be linear-planned and controlled.

Conceptualized dichotomy between exploration and exploitation first coined by March (1991), has since acquired significant traction in innovation management (Rojas-Córdova et al., 2023), but recent studies have raised doubts as to whether exploration and exploitation are separable or whether they are inevitably intertwined in practice (Rojas-Córdova et al., 2023). Killen et al. (2023) examined how organizations manage and integrate exploration and exploitation across their innovation project portfolios and found that ambidextrous capabilities are required for organizations to innovate and succeed in today’s rapidly changing competitive environment. Their multiple-case study of six large organizations showed how the inherent pull between the formality versus flexibility in managing innovation project portfolios and organizational ambidexterity are joined.

They identified four integration mechanisms that improve ambidexterity in the innovation portfolio by embedding processes that transition from exploration to exploitation and cross-fertilize knowledge to build an innovation capability across the approaches (Killen et al., 2023). The Project Management Institute (PMI, 2017) acknowledged that waterfall was inadequate for ICT-enabled projects, by incorporating an Agile Practice Guide in to the PMBOK Guide, and as such, agile adoption in software teams increased from 37% in 2020 to 86% in 2021 (Digital.ai, 2022). However, DSIs go beyond software development: they incorporate a large element of data uncertainty, scientific discovery and continuous learning and assume a greater level of flexibility than agile software projects would typically assume (Saltz & Shamshurin, 2016).

2.2 Unique Characteristics of DSIs

Recent research also brings several novel, distinctive features of DSIs that challenge earlier accounts of management (Mathur, 2024; Ridouani, 2024). First, DSIs have uncertain objectives and paths: there may be clarity on the business problem, but on the solution and the data to attain the solution, uncertainty starts late in the project. Second, data quality and data availability is uncertain: a desired attribute may only emerge when the complete dataset is ingested and analysed so that early planning is necessarily very speculative. Third, requirements are volatile as business rules, data sources, operational systems can change over time, which means adaptation in contrast to specification. Fourth, DSIs are interdisciplinary, bringing together collaboration across data scientists, engineers, end users, change managers, thus introducing issues of coordination rarely encountered in typical ICT projects. Fifth, DSIs are oriented towards a product lifecycle (versus a one-off delivery): DSIs require ongoing maintenance and model retraining and constant improvements and therefore project-based funding and end to a project are inappropriate. Sixth, benefits are often difficult to estimate at an upfront; so optimism bias exists and unrealistically high financial expectations happen (Flyvbjerg, 2023). These six characteristics make traditional governance structures, business case formats, and delivery methods irrelevant (Xu, 2024; Alabi et al., 2023).

2.3 Governance and Agile Frameworks

Traditionally, governance favours control, detailed upfront planning and annual budgeting cycles. Such traditional governance is unsuitable for the dynamic nature of DSIs (Rigby et al., 2016). Agile governance, by contrast, favours customer centricity, team empowerment and iterative value delivery: it enables quicker responses to change (Lappi et al., 2018). Scaled agile approaches (in particular, the Scaled Agile Framework (SAFe)) recommend organising around value streams, funding teams rather than projects, and lean budgeting with guardrails to allow empowered decision-making (Scaled Agile, 2023). SAFe portfolios link strategy and execution through Lean Portfolio Management, which encapsulates investment strategy

and finance, agile portfolio operation and lean governance (Scaled Agile, 2024). SAFe provides the funding, strategy and will of the market, the minimum necessary governance needed and it makes the decision-making decentralised (Scaled Agile, 2023).

"Minimum Viable Governance" (MVG) has also emerged as a realistic answer to balance governance's control with flexibility in agile settings. Mathur (2022) also did an exploratory study of governing for DSIs from a single case study of Transport for New South Wales and explored agile governance at project, program and portfolio level, and gave eight guidance principles which focus on product and portfolio governance. MVG is described as being that only those rules, processes, roles, controls that are needed for a team or organisation to perform and work safely, compliantly, effectively and in concert, without slowing down innovation and delivery speed are introduced (InLoox, 2024). This type of governance entails a very lightweight, modular, iterative governance platform that matures with the system maturity, mission-criticality and real world usage of the system (Orangeslices, 2025).

Research on agile governance has also developed adaptive governance models that contrast with the mechanistic approach to command and control (Sanz et al., 2023). Such models, on Agile Portfolio Management with a socio-technical perspective, help organisations to respond to the strong pace of change induced by digitalisation. New governance models in agile organisations focus on leadership of teams, strategy alignment with execution and embedding governance within continuous delivery rather than adding it as an afterthought (ProjectManagement.com, 2025). Best practices for this include defining a"minimum viable governance"as light touch rules that assure compliance without burdening teams, and integrating governance within agile ceremonies (portfolio reviews, PI planning and retrospectives) (ProjectManagement.com, 2025).

2.4 Data Science Process Models

CRISP-DM — the Cross-Industry Standard Process for Data Mining — continues to be the de facto choice for structuring data mining projects, because of its industry-neutral adaptability (Chapman et al., 2000). The six phases of the CRISP-DM process, namely Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment, allow the modelling work to proceed in an organised way (Gerhart et al., 2023). Yet, with analytics being widely used, teams being larger and evolving, the communications in the CRISP-DM process and understanding among additional parties becomes more necessary than ever. Gerhart et al. (2023) advocate updating the CRISP-DM process to a more Agile-inspired approach that puts emphasis on the parties and their interactions among one another, through using shorter sprints throughout the CRISP-DM process and engaging stakeholders better so as to generate better outcomes.

One SBC Reviews (2024) literature review analysed the developments of CRISP-DM for data science by examining 16 featured models, taking a closer look at the similarities and differences between the CRISP-DM derivatives, and how CRISP-DM has moved from stiff processes to agile methods. At the same time, the literature on hybrid models which cover the CRISP-DM process with well-defined time-limited sprints present the way that changes of requirement can be proactively dealt with by a mixture of Agile-Scrum CRISP-DM method while still ensuring product goal can be delivered (OnePetro, 2024). Yet, the literature still lacks a generalized, empirical practice framework that couples program management, agile delivery, data management and data science process for DSIs as a whole (Mathur, 2024). The literature mentioned in this study does just that

3. Methodology

Our study features a qualitative multiple-case study approach, following interpretivist philosophy and an abductive approach (Yin, 2018; Dubois & Gadde, 2022). Our unit of analysis is the individual DSI, as embedded subunits are governance events, program artefacts and stakeholders. Seven DSIs implemented in Transport between 2017 and 2022 were chosen via purposive sampling based on replication logic: this can be both literal replication (prediction of similar outcomes) and theoretical replication (prediction of opposite outcomes for obvious reasons) (Yin, 2018). The cases we choose are very different in size, complexity, success or failure - ranging from early failures like the CTABS initiative to successful mature ones like Active Transport project - so do have rich information power (Malterud et al., 2016) and support robust pattern matching.

Three complementary sources were used to gather data. In semi-structured interviews with programme managers, data scientists and executives, we obtained 22 in-depth interviews. The researcher also attended participant observation at governance meeting, sprint retrospective and steering committee meetings throughout the duration of the study. Finally, archival document analysis of business cases, RAID logs (Risks, Assumptions, Issues and Dependencies), JIRA and Confluence records and internal emails was done in detail. This resulted in triangulation and comprehensive understanding of each DSI's lifetime.

Our analysis of data proceeded via systematic coding using NVivo. Initial open coding identified recurring themes

and these were grouped in categories and linked to theoretical constructs such as ambiguity, governance flexibility, skills adequacy etc. Pattern matching and explanation building was used to test our propositions and establish causality (Yin, 2018). We relied on member checking and triangulation of different sources of data for credibility, and employed a detailed audit trail to guarantee dependability (Lincoln & Guba, 1985). Ethical approval was granted by both the university ethics review committee and by the organisation's own board of governance. All projects and participants were pseudonymised. Informed consent was obtained from all participants in the interviews and everybody has a right of withdrawal.

4. Findings

4.1 Why Traditional Approaches Fail

Across all seven cases, we saw three overarching modes of failure, whenever "traditional program management practices" were applied. The first was failures relating to business cases: detailed, upfront estimates of costs and benefits were consistently unreliable. For both the Vanguard and CTABS initiatives, costs were almost always underestimated and benefits were too overestimated — "delusional optimism," as Lovallo and Kahneman (2003) call it. Because teams couldn't accurately forecast data quality or model performance before ingestion, they couldn't provide realistic budgets or timelines, so projects were forced to reduce budget and scope mid-project and eventually compromised the value of the initiatives. Our finding is consistent with the systematic review on big data project failures by Ataei et al. (2024) finding financial and methodological constraints as the two major themes in those project failures.

One of the two failure modes was governance rigidity. Annual budget cycles were ill-suited to the two-week sprint cadence so characteristic of agile data science work, inflicting constant friction in decision making. Monthly steering committee meetings were too slow to approve necessary pivots, inducing delays and loss of momentum. As do Christoph Loch and Sommer (2023) point out, managers would probably tighten control in the face of uncertainty, but such a response only further stymied experimentation and fast learning. This conclusion is consistent with Sanz et al. (2023) that digitalisation imposes a powerful pace of change that demands adaptive governance models moving away from a mechanistic command-and-control style of governance.

Our third failure mode was waterfall delivery, which failed to accommodate the iterative nature of data discovery. The Vanguard project originally intended a linear sequence of phases. However, during modelling phase work, as anomalies appeared in the data, the team had no choice but to rework earlier stages, resulting in spectacular schedule overruns. It was only when the team dropped waterfall and became iterative based on CRISP-DM, that the project managed to make progress. Similarly, Haertel and colleagues (2024), in their case study of a data science project at a European Original Equipment Manufacturer, encountered problems in applying traditional process models for data science activities and highlighted for new DS project processes to be developed and evaluated.

4.2 Confirmation of Unique Characteristics and the Critical Role of Skills

The six unique properties identified from the literature were all apparent in each of the seven cases. For example, in PTIPS Analytics, it was unknown what the data quality would be when data were ingested — it confirmed the characteristic of data uncertainty. In Light Rail Priority, requirements changed continuously as new operational data sources were introduced — it was an example of dynamic nature of DSI scope. The interdisciplinary nature was evident in every case: for coordination between IT, operations, policy-makers, and outside vendors. These findings resemble those of the systematic literature review by Lahiri and Saltz (2024) that found that big data execution issues and the need for risk management practices specific to large-scale data science projects are persistent problems.

By an element-by-element comparison of the seven cases, we observed that the skills gap was the single most important determinant for success, out-weighting technology complexity, data complexity and budget size. The early cases, Vanguard and Ferry, had very high levels of stakeholder and technology complexity and very high requirements uncertainty, but suffered only partially or moderately as a result of medium levels of the skills gap. By contrast, CTABS, with only low and/or medium levels of technology and stakeholder complexity had the largest skills gap of the seven cases, which ultimately led to complete cancellation of the project. The later and more mature cases, PTIPS Analytics, Light Rail Priority, MPR and Active Transport, were all distinguished by low levels of the skills gap. Even though the case of Active Transport had very high levels of stakeholder, data and technology complexity, this project's well resourced and well capable team was able to deliver considerable business value.

As this pattern shows, if organisations make an investment in establishing the appropriate data science and program management capabilities, they can actually successfully manage even the most complex DSI environments.

4.3 The Evolution from Exploration to Exploitation

There was also a clear chronology running from the early cases through the later cases. The first three examples — Vanguard, Ferry, CTABS — were high-uncertainty, immature organisation with ad-hoc governance. As organisation maturity improved, the later cases — PTIPS Analytics, Light Rail Priority, MPR and Active Transport — increasingly leveraged scaled agile methods, lean portfolio management and (institutional) knowledge around DSIs and the need for exploration-friendly practice. Such an evolution and integration emphasise the integrated mechanisms we identified by Killen et al. (2023) who found embedding processes for transition from exploration to exploitation and cross-fertilisation of knowledge can build innovation capability across the approaches. However, even at the exploitation stage, uncertainty around data and algorithms remained high; the exploratory aspect never gone away, but it could be better handled with adaptive governance and iterative funding. The finding confirms that DSIs are not one-off projects but are evolving product-like ventures that call for continuous and flexible monitoring.

5. Discussion

5.1 A New Framework for Managing DSIs as Exploratory Projects

Based on these findings, our paper advocates an evidence-based delivery framework that integrates 5 key domains: programme management (following the PMI standard), change management (based on ADKAR and the Kotter models), scaled agile (SAFe), data management (following the DAMA-DMBoK) and data science processes (CRISP-DM). This integrated framework addresses gaps found with any single, traditional approach by making the framework iterative, based on use of SAFe lean portfolio management events such as strategic portfolio reviews, portfolio syncs, participatory budgeting to help reach rapid adaptation (Scaled Agile, 2024). It also replaces highly detailed NPV-based forecasts with hypothesis-driven lean business cases that fund early tests and allow for iterative investment decision making on the basis of evidencing new insights. It also moves from project-based to product-centric funding from ongoing value streams that deliver the outcomes of interest, rather than to discrete investments, so that DSIs can get ongoing support and maintenance and evolution of models that they need.

Integrating CRISP-DM with agile methodology is particularly important. As Gerhart et al.2023 felt, working short sprints throughout the CRISP-DM process has the advantage of engaging stakeholders better and leads to better outcomes. Initiating the process with an expectation of change can also improve the modelling process and diminish frustration amongst analysts and stakeholders when there will inevitably need to be changes. This hybrid approach, which fits the CRISP-DM process within fixed time-limited sprints, highlights how we can manage changes to requirements strategically and how we can ensure that we reach the product goal (OnePetro, 2024).

5.2 Minimum Viable Governance (MVG)

At the heart of our proposed framework is the concept of Minimum Viable Governance (MVG) – which we define as the bare bones set of policies, processes and decision-making mechanisms necessary to ensure accountability, risk management and value delivery, yet still give the team a high level of freedom to experiment and learn (see Mathur, 2022; InLoox, 2024 for discussion). As with SAFe (2023) and the "Goldilocks principle" (Holtermann et al., 2019), the idea of MVG follows eight guiding principles which together constitute an integrated governance philosophy. First, organisations should organise teams around enduring value streams instead of based on functional silos, as value streams create a natural boundary for enabling end-to-end delivery of business value (Scaled Agile, 2023). Second, money should be allocated to these value streams instead of individual projects, lean budgets and appropriate guardrails that allow teams to make decisions without needing too many approvals:

Third, portfolio Kanban with work-in-process limits is needed to visualize and to manage the flow, avoid overload, and ensure that demand fits actual capability. Fourth, prioritization needs to use WSJF weighted with cost of delay (weighted shortest job first) which ensures that the most valuable work gets done first. Fifth, decision-making needs to be decentralized to empowered teams, as central decision-making slows down adaptation and limits innovation (ProjectManagement.com, 2025). Sixth, performance needs to be tracked on flow, outcomes and competence rather than simply on adherence to plans, because in exploratory work, learning and value delivered is more important than schedule compliance. Seventh, the approach needs to embrace progressive elaboration, iterative experimentation, acknowledging that both requirements and solutions will co-evolve in time. Eighth, continuous contact with the business owner needs to be maintained throughout the lifetime so that the work is considered for overall strategic objectives and allowed fast feedback.

This study's MVG approach connects with the idea of 'governance ambidexterity' identified by recent work (Sanz et al., 2023) in that organisations need to balance traditional governance practices with agile ones to properly govern digital

change. In the Active Transport case, taking this approach meant that we could be able to do quick course changes, minimise bureaucratic overhead, gain buy-in from a diverse set of stakeholders; a monthly portfolio sync scrapped the cumbersome annual steering committee; and the WSJF tool also made prioritisation fair and effective, across numerous competing DSIs.

5.3 Implications for Practice and Policy

For program managers, this framework offers clear next steps: use agile and scaled agile approaches, invest in onshoring their skills, shift from a project mind-set to a product mind-set. For policymakers and organisational leaders, this set of findings calls for reforming procurement cycles and budget cycles to allow for iterative, discovery-led investment, not insisting on a fully detailed plan before any funding is released. For academics, this work makes the important bridge between project management theory and the emerging field of data science, presenting a solid platform for future research on managing uncertainty and innovation in technology-intensive programmes. It also contributes to the literature on managing risks for data science programmes and projects, as Lahiri and Saltz (2024) and Ataei et al. (2024) have recently recommended.

5.4 Limitations and Future Research

This study has been limited to one public sector organisation in the transport domain and this may impact generalisability of results. Future research will test the framework across private sector firms and in other public sector contexts, such as healthcare and energy. In addition, whereas our current study focused on qualitative evidence, future quantitative surveys could be used to test statistical associations between MVG adoption and DSI success rates across larger samples. Moreover, longitudinal studies involving tracking of DSIs from ideation to decommissioning will further develop the evidence base and capture these full lifecycle effects. Further, as Haertel et al. (2024) point out, extension of research to other project phases and additional cases are required to generalise the findings.

6. Conclusion

Its potential to transform organisations is massive, but these data science initiatives continue to fail at an alarming rate, with rates of failure as high as 80% and as high as over 90% even on organisations that are fairly mature in their approach to data science (Shellshear, 2024). In this paper, we have shown how the main cause of this failure is the wrong methodology that people use, namely traditional program management paradigms, with exploratory, uncertain and iterative DSIs. Establishing that there are 6 differentiating characteristics and proving empirically this for 7 in-depth case study research is very convincing evidence for a completely different approach. This proposed evidence-based delivery approach and Minimum Viable Governance concept are very practical and empirical validated solutions that enable organisations to manage DSIs as exploratory projects, with flexible governance, lean business cases, product-centred funding. Adopting such approaches could drive value realization and avoid waste. Organisations are rapidly becoming more data-driven, so it is not a question of whether they adopt these principles — it is a question of whether they can survive and succeed in the new digital economy.

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