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The mindless behaviours of the Data governance Naïveté Trap: a case study

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ABSTRACT
Access to quality data is crucial for business processes, and an effective Data Governance (DG) programme aims to ensure that this happens. However, an examination of industry literature suggests that the implementation of DG programmes continues to present challenges for practitioners. This is despite academic research having developed a large body of DG knowledge and potentially useful artefacts. This case study explores this disjoint by focusing on people's behaviours and how they impact the DG programme. It surfaces root causes for the ineffectiveness of a DG programme. It emerges that a lack of constant review and revision of DG principles results in the organisation being caught in what we refer to as the DG Naïveté Trap.

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1. Introduction

Data Governance (DG) is a topic which has relevance for both the academic and practitioner communities for upwards of 25 years (Abraham et al., 2019; Al-Ruithe et al., 2019; Alhassan et al., 2018; Otto, 2011a). However, despite being an established field of study with a significant body of knowledge, DG continues to be challenging to operationalise effectively in practice (Redman, 2025). This assessment is corroborated by IS researchers, with several of the extant academic case studies also reporting issues encountered by DG programmes in practice (Benfeldt et al., 2020; Lee et al., 2019; Lis & Otto, 2020; Tallon et al., 2013). The issues persist despite an abundance of artefacts, specifically frameworks, contributed by IS research (Al-Ruithe & Benkhelifa, 2017; Yebenes & Zorrilla, 2019) Weber et al. (2009); Khatri and Brown (2010); Alhassan et al. (2018). These frameworks offer a useful foundation for all DG programmes and can be supplemented with the outputs from several studies proposing critical success factors (CSFs) for effective DG (Alhassan et al., 2018; Brous et al., 2020). However, notwithstanding the availability of these resources, DG programmes continue to experience problems and challenges (Benfeldt et al., 2020; Chakravorty, 2020; Vial, 2023).

The challenges observed in previous DG case studies include lack of trust and clarity around data ownership (Lis & Otto, 2020), poor collaboration across silos, general scepticism towards DG (Benfeldt et al., 2020), and poor monitoring and data classification (Lee et al., 2019). The practice literature also highlights a lack of an understanding of what DG actually is, and the criticality of assigning the right people to the DG programme and properly training them (Maren, 2024; Redman, 2025). It is also well documented that the attitudes and behaviours of the DG team are pivotal to the likely outcomes (Eybers & Setsabi, 2021; Nielsen et al., 2018; Parmiggiani & Grisot, 2020; Tallon et al., 2013; Walsh et al., 2025). DG case studies tend not to conduct a detailed exploration of the root causes for these challenges. Also, they do not usually propose solutions for the problems observed beyond critical success factors. Therefore, we propose that an exploration of data consumer behaviours and how they might be contributing to the DG challenges may lead us closer to resolving some of these issues. In this paper, we ask the following research question.

RQ: *What are the mindless behaviours and how do they hamper the effectiveness of a DG programme?*

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This paper details a case study conducted in a large educational organisation (UniOne) to examine their current Data Governance (DG) programme and practices. The purpose of the study is to explore any ineffectiveness in UniOne's DG programme. It focuses on the organisational elements and mindless human behaviours (through the lens of Organisational Mindfulness (OM)) around the data practices which may be hampering the achieving of the organisation's operational and strategic goals. For the purposes of this work, mindless behaviours are those where individuals are either unaware of alternative possibilities, or do not look for these other options when they encounter issues in a business process or operations. Instead they tend to go into 'automatic pilot' and fall back on past experience, or company culture (Walsh & Ungson, 1991). This study explores the root causes for these behaviours.

The remainder of this paper is structured as follows. The theoretical background presents an overview of the DG and OM literature and presents the Organisational Mindfulness Data Governance (OMDG) conceptual model which forms the theoretical foundation for this study. The research approach describes the process used to gather and analyse the data. This is followed by the presentation of the results from the open and axial coding phases. The discussion section then presents the output from the selective coding and forms our hypothesis for the root cause(s) of the mindless behaviours that hamper the effectiveness of a DG programme. Finally, the paper concludes with a conceptualisation of the *DG Naïveté Trap* and suggestions for future research.

2. Theoretical background

This study will use Organisational Mindfulness (OM) to highlight those behaviours that are detracting from Data Governance (DG) programme effectiveness. Therefore, in this section we explore both DG and OM in detail. The section concludes by introducing our OMDG conceptual model which is used to analyse our case data.

2.1. Data governance

While there is no one universally accepted definition for Data Governance (DG), a widely accepted interpretation is that it relates to the assignment of decision-making rights and responsibilities for an organisations data assets (Benfeldt Nielsen, 2017; Khatri & Brown, 2010; Otto, 2011b). DG has emerged from the growing acceptance of the concept that data is an asset which the organisation needs to protect (Otto, 2011c; Panian, 2010). The DG programme is designed to guide the human actors in their engagement with the organisational data (Benfeldt et al., 2020; Chakravorty, 2020; Lis & Otto, 2020) and DG is often implemented to manage the data used by the organisation for both operations, and strategic decision making (Weber et al., 2009). The DG policies and procedures help to ensure that the data is kept secure, is of good quality, and is used and understood in a consistent manner by all members of the organisation (Batini et al., 2009; Karkoskova, 2023; Otto, 2011c). Furthermore, it must be seen as a long term commitment that is constantly monitored and refined over its lifetime (Alhassan et al., 2018; Walsh et al., 2025).

A successful DG programme has many benefits for the organisation; principally the value of the data asset can be maximised (Otto, 2011b). This is achieved by ensuring the quality is both improved and maintained where necessary, providing everybody with a common shared understanding of data's meaning, and making it easily accessible to those that might need it (Gegenhuber et al., 2023). All of this provides for more efficient and more effective decision making. DG programmes are developed with well-intentioned principles, but their real benefit to the organisation emerge when they are operationalised (Barrenechea et al., 2019; Brous et al., 2020; Mikalef et al., 2020). However, implementation is a non-trivial task as it often requires a change to the way of working for many data users (Benfeldt et al., 2020). While the technology component is generally relatively straightforward, people's natural tendency to resist change poses the greatest challenge to DG implementation (DAMA International, 2017). Abraham et al. (2019) advises that all decisions made during the design of the DG programme should consider the context of the target organisation.

A key element to consider when designing DG is the adoption of a suitable framework. We favour the DG activities model from Alhassan et al. (2018) as it incorporates the five 'decision domains' from Khatri and Brown (2010), namely: *data principles*, *data quality*, *data access*, *metadata*, and *data lifecycle*. We appreciate how Khatri and Brown (2010) presents the complexity of DG theory in the form of these five decision domains or themes. Themes such as data quality, data access, and data lifecycle are familiar to data practitioners, and are therefore viewed as relevant to practice. We feel this greatly improves the likelihood of practitioners embracing DG. The ubiquitousness of the Khatri and Brown (2010) framework from which they are drawn, combined with their simplicity also makes them ideal for use in empirical research (e.g. shaping a case study interview guide and selecting conceptual bins for data analysis). We also favour the DG activities model because it introduces three phases for a DG programme, namely: *define*, *implement*, and *monitor*. These DG implementation phases offer useful milestones for programme teams charged with operationalising DG. It also allows us, as researchers, to better understand where in the DG programme cycle the bad practice(s) and ineffectiveness begins to appear.

2.2. Organisational Mindfulness

The use of a mindfulness lens when analysing IS research data has proven to be a useful approach for examining people's behaviours (Swanson & Ramiller, 2004). Organisational mindfulness helps to make sense of the 'messy realities' likely to be found in many organisations (Weick et al., 1999). Mindfulness is an approach to reliably discover and manage unexpected events; the opposite being mindlessness, where the individual goes into 'automatic pilot', falls back on past experience, or company culture, and is unaware of alternative possibilities (Walsh & Ungson, 1991). While instinctive and automatic behaviour has some benefits (Levinthal & Rerup, 2006), the use of restricted viewpoints can have severely detrimental effects when employed mindlessly to solve new problems (McAvoy et al., 2013; Weick & Sutcliffe, 2006). The fast pace of change in information and data technology does not lend itself to mindless problem solving. A mindful organisation is better placed to adapt to innovations as they are more resilient and less likely to become fixated on the initial plan (Mu & Butler, 2009). Mindful organisations exhibit several behaviours which set them apart. Weick et al. (1999) developed a list of the five behaviours typical of a high performing mindful organisation. They categorise their five behaviours into two groups: anticipation and failure.

Anticipation includes *preoccupation with failure*, *reluctance to simplify* and *sensitivity to operations*. Through their *preoccupation with failure* mindful organisations remain alert to potential issues, encourage the reporting of problems, and consult the right people to detect failures before they escalate. They are *reluctant to simplify interpretations* because they recognise that overly simple explanations can mask anomalies. They promote curiosity about the unexpected and acknowledge what they do not know. Moreover, their *sensitivity to operations* ensures continuous situational awareness, enabling regular small adjustments to prevent errors and avoid automation surprises as well as verifying that actions lead to safe outcomes.

Containment includes *commitment to resilience* and *deference to expertise*. Mindful organisations display a strong *commitment to resilience*; they strive to predict and manage errors effectively. They do this by forming ad hoc expert teams to resolve problems and continuously learn from past mistakes. Their *deference to expertise* ensures that decision-making is flexible rather than hierarchical, authority shifts to those with the most relevant expertise so that the right people make the right decisions in the moment.

To conclude this section using an OM lens in the context of a DG programme leads us to propose the Organisational Mindfulness Data Governance (OMDG) conceptual model to help identify the impactful relationships between DG domains and OM behaviours.

2.3. The OMDG conceptual model

The OMDG conceptual model (see Figure 1) is a matrix consisting of a row for each of the five DG decision domains and a column for the five OM behaviours. The columns for each of the OM behaviours are further divided into to two sub-sections, one for mindful behaviours which have a positive impact on DG operations, and another for mindless behaviours which have a negative impact. It is likely that some OM behaviours are more prevalent than others and that they impact more significantly on certain DG decision domains. This in turn will provide the focus for a more detailed examination of the relationships between each pair of DG and OM elements to surface their root causes. In effect, our OMDG conceptual model summarises the current

	Anticipation						Containment				
	Preoccupation with Failure		Reluctance to Simplify		Sensitivity to Operations		Commitment to Resilience		Defer to Expertise		
	Mindful	Mindless	Mindful	Mindless	Mindful	Mindless	Mindful	Mindless	Mindful	Mindless	
Data Principles	1	6	1	7	4	35	12	47	3	6	122
Data Access	1	6	1	10	16	51	19	45	4	8	161
Data Quality	14	25	6	20	17	59	18	22	2	14	197
Metadata	0	1	0	4	1	12	4	3	5	11	41
Data Lifecycle	0	5	1	11	6	42	16	44	2	11	138
	16	43	9	52	44	199	69	161	16	50	659

Figure 1. The UniOne OMDG conceptual model story.

state of the DG landscape within an organisation. For example, cells with a high score highlight a combination of DG decision domains and OM behaviours which are especially prevalent, and potentially problematic, within an organisation. These 'hotspots' are then used as the focus for initial cycles of causal analysis to dig deeper into what is happening on the ground. Therefore, the OMDG conceptual model enables us to organise, visualize, and explore the coded data. In the next section we outline the research approach and how our causal analysis is conducted.

3. Research approach

In this paper, we present a case study of an organisation and its current DG practices. The case study method is used as it allows the study of the subject in its natural setting. It is particularly suited to the study of people, groups, or organisations using qualitative data (Benbasat et al., 1987; Galliers & Land, 1987). The data in this study consists of semi-structured interviews conducted with a stratified sample of data users in UniOne. The interviewees were chosen to represent a cross-section of data users in the organisation who are experts in their respective roles. The interviews were transcribed and coded using an open, axial, and selective coding approach. The empirical data gained from the coding phase was then unpacked to explore the current state of DG in the subject organisation.

This section begins with an overview of the case study organisation (UniOne) to provide context. It then presents the data gathering and coding process followed in this study.

3.1. The UniOne case

UniOne is an educational organisation which employs over 3,000 staff. It is currently undertaking a digital transformation programme to modernize its fragmented legacy data systems. Its current IT architecture consists of a hybrid cloud configuration consisting of legacy on-campus data centres for functions like the Registry combined with modern Software-as-a-Service (SaaS) solutions for other business lines, such as Human Resources and Student Applications. This hybrid architecture model creates an increased emphasis on data integration chiefly because primary SaaS systems must support both specialised niche applications and a central data warehouse used for historical reporting. Despite the increasing complexity of their data landscape, UniOne's strategic response appears to overlook the realities of modern data management. Their recently published Digital Strategy does emphasise the role of technology and data in their future success. However, it is notable that DG is conspicuously absent. Currently the IT department maintains the physical infrastructure, while data policy is the responsibility of individual business functions. This arrangement has enabled the emergence of 'functional silos' (Vial, 2023), leading to inconsistent management standards with varying levels of data literacy across departments and a patchwork of policies. One good example of the negative effects of this lack of a coordinated DG approach is how it has resulted in cumbersome procedures for requesting cross-functional data access. There are no indications from the Digital Strategy that the status-quo is going to change. All of this suggests that UniOne's traditional DG approach is no longer fit for purpose in a modern hybrid ecosystem.

3.2. Data collection and coding

A stratified sampling approach was employed, with the interviewees selected to represent a cross-section of the organisation's data user community based on their roles, responsibilities and expertise. By selecting participants with diverse perspectives the risk of any bias is reduced (Eisenhardt & Graebner, 2007; Williams & Wynn, 2018). In total 44 potential interviewees were identified and invitations to participate were issued. Positive responses were received from 17 invitees; the informants who agreed to participate are representative of those with responsibility for DG activities in UniOne. They can offer good quality responses which is more important than the quantity of responses in this case. Interviews were conducted over a period of 16 months between April 2023 and August 2024. The informants represent a range of data roles across key functional areas in UniOne. They come from the IT Data Team (2), Application Administrators (4), the Student Services Team (3), the Policy Development Team (3), the Finance Team (3), and Unit Managers (2). These informants offered unique strategic and operational perspectives on student-facing processes, and data-driven decision-making. The interviews are transcribed, and coded using an open, axial, and selective coding approach (Alhassan et al., 2023; Wolfswinkel et al., 2013). The open coding phase parses the transcripts into individual excerpts, typically the response to question or a follow-up question prompted by a previous answer. Each excerpt is assigned both an OM behaviour category and a DG decision domain. The excerpts are then organised using a multi-step process. Firstly, they are divided along the five decisions domains of Khatri and Brown (2010) previously used to structure the interviews. The process of sorting by decision domain is useful to gain an initial view of what the interview excerpts tell us. However, in order to gain a deeper understanding of what is happening a series of open coding cycles are conducted (Alhassan et al., 2023; Wolfswinkel et al., 2013). Each interview excerpt is next coded to one of the five mindful behaviours from Weick et al. (1999). During this cycle of coding the behaviours are tagged as either mindful (positive contribution to DG practice) or mindless (negative contribution to DG practice). As an example of mindful behaviour, one informant talks about experiencing data quality issues with a data feed between systems. To address the issue, they called a meeting of the appropriate systems administrators and developed possible remedies. By contrast another informant described an ongoing data quality issue caused by the lack of validation in a data input form. However, they felt that because the data originated from a 3rd party, they had no power to influence change and instead they invested a significant amount of their time cleansing the data. This was coded as a mindless behaviour because no attempt was made to escalate the issue outside of the team and confirm or refute their assumptions. The behaviours are also categorised based on how frequently they occur; for example, those that occur daily or weekly are coded as high frequency and any that happen monthly or less often are low frequency. In addition, an assessment is made of how impactful the behaviour is on DG, and they are further divided into low and high impact groups. A behaviour is considered low impact if it only affects one team, or a single system, or occurs infrequently. On the other hand, a high impact behaviour is one that for example has a knock-on effect outside of the department where it occurs, or where it happens repeatedly and consumes a lot of the team's time. The axial coding phase then organises the results based on the relationships between the open coding categories. This produces the completed OMDG conceptual model (see Figure 1). For the selective coding phase, the data is analysed to surface the root causes of the behaviours identified in the previous two coding phases. Periodic checks were routinely carried out throughout the coding process (by the three-person research team) to ensure the robustness of the coded outputs.

4. Results

The open coding of the results examined the 17 interviews and parsed them into individual excerpts. An excerpt represents a discrete data point, typically the answer to one interview question. Some answers are sub-divided into multiple excerpts where the answer discusses more than one behaviour or issue. The initial questions are organised around the five DG decision domains from Khatri and Brown (2010). In total 659 individual excerpts are catalogued. Each excerpt is then examined through the lens of OM and is assigned to one of the OM elements. The open coding phase results in the 659 excerpts being assigned to one of the 50 groups based on their DG decision domain, the OM behaviour element, and whether they are mindful or mindless behaviours. The axial coding phase organises these 50 categories to expose the relationships between them and build the completed conceptual model (see Figure 1). While there are a mix of mindful and mindless behaviours it is evident that in most OM categories the mindless behaviours predominate.

There is a noticeable clustering in the sensitivity to operations and commitment to resilience behaviours and in these two categories the mindless variant constitutes just over 76% of the actions.

These mindless traits are evident in the data access, data principles and data lifecycle decision domains. While data quality does also display some issues around sensitivity to operations there is not the same level of mindless behaviour in the commitment to resilience category. It is also notable that metadata does not feature to any great extent in the excerpts. The effect of mindless behaviours however cannot be assumed to be homogeneous. Some tasks are executed daily or weekly and consume a large proportion of an informant's work schedule, while others are smaller and annual or semi-annual in nature. Similarly, their impact on the performance of the organisation can vary. Therefore, we focus our investigations on those behaviours which have the greatest negative effect. Arguably the greatest benefit can be achieved for the organisation in addressing this sub-set of behaviours in the first instance when designing DG programmes. Using the frequency and impact classifications assigned to each excerpt during coding it is possible to identify these problematic behaviours in each decision domain by isolating those which are both high frequency and high impact in nature (see Figure 2). This refinement of the high-level results shows that only 27 of the 45 mindless behaviours for commitment to resilience in data access are high frequency and hight impact. A similar breakdown of the results based on frequency and impact for each of the decision domains is produced (see Figure 3). The hot spots in this reduced data set tallies with the findings of the high-level analysis seen in Figure 1. The issues described by the informants are centred around the commitment to resilience and sensitivity to operations behaviour types distributed across four of the DG decision domains, namely data access, data quality, data principles and data lifecycle. The causes of these issues and the related behaviours are now explored in more detail.

The empirical data is examined to uncover the key high frequency and high impact mindless behaviours (see Table A1 in Appendix 1). To gain a better understanding of the reasons for these behaviours a hypothesis proposed and tested using the method adapted from Runde (1998). These hypothesis testing cycles are repeated several times to discover the cause for each of the mindless behaviours. We now present a summary of our findings from this process.

4.1. The restrictions, workarounds, and bottlenecks of data access

Informants report several challenges accessing the data they need to complete their work because of data security policies. A data management model has evolved in UniOne where data owners and systems administrators manage systems with an emphasis on operations within their own department. Data ownership rights are typically assigned based on the organisations General Data Protection

		Sensitivity to Operations				Commitment to Resilience			
		Impact				Impact			
		Low		High		Low		High	
		Mindful	Mindless	Mindful	Mindless	Mindful	Mindless	Mindful	Mindless
Frequency	High	2	9	**10**	**36**	4	9	**12**	**27**
	Low	2	5	2	1	1	6	2	3

Figure 2. 'Data access' excerpt frequency and impact analysis.

	Anticipation			Containment	
	Preoccupation with Failure	Reluctance to Simplify	Sensitivity to Operations	Commitment to Resilience	Defer to Expertise
Data Access	2	8	36	27	7
Data Quality	10	12	35	13	8
Data Principles	3	4	21	29	4
Data Lifecycle	0	6	22	19	7
Metadata	1	2	9	0	6

Figure 3. 'High impact' & 'high frequency' mindless behaviours.

Regulation (GDPR) policies. This devolved model has led to an inconsistent and often ineffective patchwork of data access rules across departments. The decentralised model also means that no one person has a holistic view of the data access issues or indeed has any idea of what is possible in terms of alternative or improved data access options. The subliminal association with GDPR can also make data owners extra cautious and this has created situations where data users in operational roles are not allowed access the data which they need to get the job done. Some people are forced to find workarounds, such as sourcing data from sympathetic colleagues. However, the policies are not the only data access problem. Many users have also found the technology to be a barrier when attempting to access data. An over emphasis on operations has resulted in operational reports being the 'go-to' for dissemination of data. However, this mechanism is wholly unsuited to users who need data sets from multiple business areas. The needs of these strategic decision makers are forgotten and results in them expending significant effort combining data sets from multiple reports using spreadsheets. Several respondents highlighted a desire for more self-service data access options that requires minimal post-processing after download. Unfortunately, there is no forum to gather and prioritise new data access requirements centrally for the whole of UniOne. Rather the continued dependence on operational reports requires users who wish to explore new data to submit change requests and join the queue for report amendments. This approach puts the organisation in the precarious position of being overly reliant on a small number of developers who have the skills to build reports. Consequently, these developers have become a bottleneck which can slow down data driven decision-making. Nevertheless, management see no obvious need for change because operations are o.k. and from their perspective *the job is getting done*.

4.2. The awareness, excuses, and workload of data quality

Many of the informants believed that the quality of the data was quite poor. Some of these data quality problems might be better described as data consistency issues. For example, the data access problems described earlier creates a situation where reports are printed off and there can be multiple versions of a report in circulation. Data discrepancies between versions are wrongly attributed to poor data quality when in fact both copies were correct at the point in time when they were printed. Nonetheless, UniOne does have some genuine data quality issues, but they often go unresolved because of poor levels of data literacy among the users. A lack of understanding of data can lead to blame for various issues, such as unreliable systems integration, being wrongly laid at the door of data quality. Some of the challenges around data integration were found to be the result of ineffective master data management (MDM). The devolved data ownership model results in uncoordinated changes to master data, which ultimately causes avoidable errors when loading data into secondary systems. This fragmented approach to MDM also creates problems for the users who depend on it to stitch together data sets for strategic analysis and decision making. The solution for many users is to devote significant amounts of their time to checking the data and manually fixing errors. This might seem like mindful behaviour, but arguably a more mindful action would be to prevent the errors in the first place by pushing for changes in policies and processes to improve the quality of the data at source. The consequence of all of this is an unnecessary additional workload being placed upon many users.

4.3. The history, focus, and fragility of data principles

The cornerstone of any DG programme are the data principles which help guide data standards and the behaviours expected from everyone who interacts with the data. The organisation does have some DG principles but crucially they are not part of a formal DG programme. They are more a collection of *de-facto* policies which have grown out of initiatives such as GDPR. This approach to DG has led to the evolution of several problematic behaviours. For instance, the priority for most data users seems to be fixing the latest problem, and there is a noticeable a lack of focus on long-term planning. Also, there is no evidence of a mechanism to learn from the problems they encounter and share the knowledge with others. On a practical level this causes ambiguity and allows situations to develop where some users block change because they are using data inappropriately and don't understand the implications of the change. Despite this they insist the current process is key to keeping operations running. One example is the lack of a DG policy to deal with exceptions. Another example is that the data ownership for the primary systems resides with the departments which originally purchased them. This ownership model has never been reviewed and in some cases the systems were procured several decades ago. The absence of suitable DG policies for ownership has created *'a culture of knowledge is power'* which has caused a myriad of problems. Overly cautious and uncooperative *gatekeepers* have emerged whose first instinct is to prevent access even for users with legitimate data needs. One informant suggested a *'data group or expert group'* to replace the current devolved ownership model which they contend has led to the emergence of these '*gatekeepers*'. They suggest that in fact the data belongs to the organisation and DG principles should assign ownership and decision rights for the good of the entire organisation. The legacy of these practices is a haphazard approach to data analytics and integration. A case in point is that there is currently no complete view of the customer because data is fragmented across systems and there is no way to submit '*wish list'* items to address the problem. Unfortunately, in the absence of a DG programme laying out policies designed to tackle these problems the *status-quo* prevails.

These results offer an insight into the principal phenomena that perpetuate the behaviours in UniOne. However, the objective is to uncover the root causes that created these phenomena (Easton, 2010; Fletcher, 2017). In the next section we will discuss our hypothesis for what the root causes might be. These hypotheses emerge from the selective coding phase. In the case of this paper, we examine the causes and the resulting behaviours with the objective of identifying the central root cause.

5. Discussion

At first glance DG in UniOne appears to be working well. The day-to-day work is getting done, deadlines are being met, and there have been no significant cyber security events. However, by digging a little deeper, we see some issues which are being hidden by the actions of what we term *busy fools*. In other words, many members of the organisation believe they are working in a mindful way and are *committed to resilience* and *sensitive to operations*. Unfortunately, by putting in the extra effort it creates a false sense of security and the underlying problems go unnoticed by management. This we argue is in fact mindless behaviour as it perpetuates problems. It is not scalable and poses a long-term operational risk if not addressed. We are searching for the root cause of the observed phenomena. We do this by developing a set of plausible candidate causal mechanisms (Wynn & Williams, 2012) for the behaviours that could prolong the observed issues. From these we build a causal framework to provide an explanation for these phenomena which are causing the mindless behaviours (McAvoy & Butler, 2018; Wynn & Williams, 2012). We contend that the issues surfaced in the interviews are due to a mistaken belief on the part of management that UniOne's DG is effective. We suggest that in fact there is no real DG in place in the organisation. Our hypothesis is that there is in fact an absence of effective data principles to guide all other aspects of DG, such as data access, data quality, and data lifecycle.

5.1. The emergence of the DG Naïveté Trap

This situation emerges from a fundamental misunderstanding of Data Governance (DG) among stakeholders. Many confuse DG which is the defining of data principles and decision rights, with data management, which is the operational execution of those principles. Senior management assumes DG is effective because the job gets done. We term this misconception the *DG Naïveté Trap*, it is a false sense of success that ignores underlying systems and process flaws. Like many organisations, UniOne sees DG as a one-off project rather than a continuous adaptive programme requiring monitoring and maintenance. Gaps in their DG are filled by extra effort from staff, masking the deficiencies and reinforcing complacency. Because work gets done, there is no perceived need for change, and the status quo persists. It must be said that some mindful behaviours do exist, users anticipate and fix recurring issues, but the focus is on short-term firefighting rather than long-term solutions. There are no structured reviews or formalised data principles guiding improvement. Consequently, energy and resources are wasted, and user resilience hides DG weaknesses, perpetuating the *DG Naïveté Trap*. Testing our root-cause hypothesis using Wynn and Williams's (2012) causal checklist confirmed the absence of effective data principles. While UniOne's IT department hosts a TOGAF-based architecture site mentioning data access, quality, and stewards, it does not define decision rights or stewardship roles. Likewise, the GDPR policy assigns compliance to department heads without clarifying DG responsibilities. This devolved ownership creates a DG regime which is largely informal and fragmented. In summary, while some data principles exist, they are insufficient and ineffective. The evidence supports this misunderstanding of DG as the true root cause rather than an intermediate issue. We will now discuss a summary of the results and demonstrate how they satisfy all three remaining questions from the causal checklist.

5.1.1. Data principles

It is notable that data ownership and systems management crops up repeatedly in the results. The three key systems are *owned* and managed by the associated business units. They are seen as the *data owners* and act as the *gatekeepers* for the data. These systems are operated largely independently in what might be called *functional silos* (Vial, 2023). There are no documented data principles setting out this data ownership model. Furthermore, the DG policy vacuum mitigates against the creation of a more accommodating approach to data access and data quality. This is largely because data custodians for the primary systems have no mandate to change existing arrangements and are reluctant to make any changes in the absence of relevant policies. Very often the systems are working well for the *owner*, and they don't want to risk breaking it for themselves. This *silo* model also has several negative side-effects for both data access and data quality. These current structures mitigate against a holistic enterprise approach to DG. Nobody has a view of the organisation-wide *big picture* in terms of the extra workload being generated by inefficiencies. An example of this is the time wasted dealing with data exceptions. For example, some data principles for dealing with data exceptions could eliminate much of the rework they generate. In addition, there is no person or group which can gather the lessons learned from projects, or the challenges faced by data users in their daily work. These lessons learned could be used to drive process improvement. The lack of a shared or central DG function also means that at present there is no custodian for the enterprise-wide master data and metadata.

5.1.2. Data access

The focus tends to be on supporting departmental operations and getting the job done. As a result, the primary data access method is via operational reports native to the systems. However, these reports are not suited to the needs of those people who require data for strategic decision making. This is especially acute where data from more than one primary system is required. To produce usable datasets many decision makers are forced to manually combine data from multiple sources. However, in the absence of suitable data principles for data access, and the fear of GDPR non-compliance, the instinct of systems administrators appears to be to prevent access to data, often without fully understanding the implications for other colleagues. The problem is compounded by the absence of any formal mechanism or forum through which the data access rights can be periodically reviewed. This mindless lack of deference to expertise means the decision rights are being assigned to managers based purely on their job role. These managers rarely if ever have an appreciation of data or DG concepts. This has led to inconsistencies in approach across systems and departments. The absence of formal shared policies has also led to lines becoming blurred between roles and responsibilities. In addition, the predominance of reports has created a dependence on a small number of developers who can build or alter reports. These developers have become a bottleneck through no fault of their own, and the access to data continues to be an issue.

5.1.3. Data quality

The manual data processing burden imposed on strategic data users results in several ensuing problems. The manual process can lead to inconsistencies and poor data quality across versions of data sets when processes change, or process steps are missed. Paradoxically while there are no documented metrics for data quality some people may use the data quality argument to stymie decisions which they do not like. The problems are exacerbated by a lack of coordinated master data management and the risk of systems administrators making unilateral changes to their own systems without due regard to other business processes which depend on them. This results in the strategic data users having to do a lot of firefighting, temporary fixes, and re-work. There is a tendency for them to duct-tape over the cracks to get the task complete. This can then cause both the producers and the consumers of the data sets to distrust the accuracy of the data, and they often feel the need to perform additional validation and checking because of their concerns around quality.

UniOne is caught in a DG Naïveté trap, an ineffective DG programme is being propped up by mindless albeit well-meaning behaviours which mask the DG programme's short comings. As a result, management does not realise that there is a need for change in the DG programme to allow them to break out of the DG Naïveté trap. The focus needs to move from 'keeping the show on the road' to determining if their approach to DG is the correct one and how it can be done better.

6. Conclusion

The results indicate that the absence of appropriate data principles has a direct causal effect on the data quality and data access issues. We argue this stems from DG naïveté, in so far as the management in UniOne have a misplaced belief that Data Governance (DG) is functioning well. When in fact without shared data principles that can evolve over time, UniOne has no mechanism to address recurring problems or deliver on users' data needs. This has created a self-sustaining cycle of mindless behaviours, where issues persist and valuable time is wasted maintaining operations rather than improving them, a pattern we term the *DG Naïveté Trap*. Although the organisation currently 'gets away with it', this approach is unsustainable as data volumes grow. There is limited capacity for strategic, cross-departmental data analysis, and a siloed culture prevails, one marked by 'knowledge is power' attitudes and resistance to sharing or change.

This study examines DG within a large educational organisation, exploring how mindless behaviours are hampering the effectiveness of its DG programme, through the lens of Organisational Mindfulness (OM). Our coding highlighted some issues on the surface around a high rate of mindless behaviours for both *sensitivity operations* and *commitment to resilience*. We went on to dig into the results to uncover the root causes of these mindless behaviours, across three DG phases, namely: *define*, *implement*, and *monitor* (Alhassan et al., 2018; Walsh et al., 2025). While the first two phases may appear functional in UniOne, the same is not true of the monitor phase. UniOne relies on continuous short-term fixes to keep the show on the road. This underestimation of the long-term effort required to sustain DG perpetuates the *DG Naïveté Trap*. To escape this *DG Naïveté Trap*, organisations must engage in regular reflection in-action and on-action, using insights to refine DG principles as part of an ongoing DG programme *monitor* phase. Without this, the same issues perpetuate year-on-year and become a time sink because of the extra unnecessary effort required on the part of most data users to complete their work. We therefore propose the following reflective practices to help organisations overcome their *DG Naïveté Trap*.

6.1. Reflection in-action and on-action

Organisations should promote regular reflection among all data stakeholders, both in-action and on-action (Schon, 1983). Reflection in-action occurs during an activity to address issues immediately, aligning with the containment aspect of OM, while reflection on-action happens afterwards to learn from and anticipate future challenges (aligning with the anticipation aspect of OM). For instance, operational data users can reflect in-action when facing data exceptions, using their expertise to resolve problems and improve data quality measures. Strategic users, meanwhile, can reflect on-action after projects, documenting data access challenges to better inform DG practices and reporting. Unlike a one-off project postmortem, this reflection is a continuous practice, embedded in daily operations and aligned with the OM component of *preoccupation with failure*. Importantly, participants are selected for their expertise, rather than their position in the hierarchy, thus honouring the *deference to expertise* OM component and encouraging knowledge sharing across roles and projects. This expertise-driven approach builds organisational resilience, mitigates political dilution of findings, and ensures insights feed directly into refining and evolving DG principles. Based on our analysis of the empirical data in this case study and our root cause hypothesis we believe that the adoption of our recommendations will improve the effectiveness of the DG programme in place in UniOne. It will facilitate a move away from the mindless containment actions seen in the observed *commitment to resilience* behaviours. We note that there are also a significant number of anticipation actions in the form of *sensitivity to operations* behaviours evident in the empirical data. However, it must be pointed out that they are predominantly mindless, high frequency and high impact in nature. We believe that the learnings arising out of reflection will promote anticipation behaviours which are more mindful and positive in nature. Mindful *sensitivity to operations* based on reflection *in action* would encourage the catching of errors in the moment. It is envisaged that it would also discourage complacency and encourage the reporting of failures to the appropriate groups, consistent with *preoccupation with failure*, as well as fostering a *reluctance to simplify*, and promoting the habit of watching out for the unusual. Therefore, processing the learnings gleaned from reflection and using them to drive improvements in DG principles will ultimately allow UniOne to break out of the *DG Naïveté Trap* and create an environment where mindful anticipation of DG issues becomes the norm.

6.2. Limitations, future research, and practical contributions

This study has some limitations. Although a stratified sampling approach was used, there remains a risk of self-selection bias, whereby participants may have been motivated by grievances; however, the diversity in roles and perspectives among informants, many of whom expressed balanced views, mitigates this concern. The reliance on a single case study also limits generalisability, as the organisation studied could be an outlier in its approach to Data Governance (DG) programme implementation. Further case-based research across a variety of organisational types and contexts is needed to assess whether the *DG Naïveté Trap* is a broader phenomenon or context-specific. Additionally, evaluating the practical impact of this study's recommendations warrants future research, ideally through longitudinal studies that could provide valuable insights for both scholars and practitioners on the anticipatory value of reflection. This research contributes to DG theory and enhances communication between the academic and practitioner communities by assisting with the translation of theory into practice (Pan & Pee, 2020; Rosemann & Vessey, 2008; Seidel & Watson, 2014; Wiener et al., 2018). This is achieved by introducing the novel concept of the *DG Naïveté Trap* to the literature and offering a practitioner-oriented perspective to help organisations break out of the *DG Naïveté Trap*.

Author contributions

CRediT: **Michael Joseph Walsh:** Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing; **John McAvoy:** Supervision, Writing – review & editing; **David Sammon:** Supervision, Writing – review & editing.

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References

Abraham, R., Schneider, J., & Vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, *49*, 424–438. https://doi.org/10.1016/j.ijinfomgt.2019.07.008

Alhassan, I., Sammon, D., & Daly, M. (2018). Data governance activities: A comparison between scientific and practice-oriented literature. *Journal of Enterprise Information Management*, *31*(2), 300–316. https://doi.org/10.1108/JEIM-01-2017-0007

Alhassan, I., Sammon, D., Daly, M., Wibisono, A., Kasraian, L., Nagle, T., Heavin, C., Dennehy, D., Zamani, E., & Qaffas, A. (2023, April 20). *The use of open, axial and selective coding techniques: A literature analysis of IS research*. UK Academy for Information Systems.

Al-Ruithe, M., & Benkhelifa, E. (2017, March 22-23). Cloud data governance maturity model. *Second International Conference on Internet of things, Data and Cloud Computing*, Cambridge, UK. Article 151. https://doi.org/10.1145/3018896.3036394

Al-Ruithe, M., Benkhelifa, E., & Hameed, K. (2019). A systematic literature review of data governance and cloud data governance. *Personal and Ubiquitous Computing*, *23*(5), 839–859. https://doi.org/10.1007/s00779-017-1104-3

Barrenechea, O., Mendieta, A., Armas, J., & Madrid, J.M. (2019, August 12-14). Data governance reference model to streamline the supply chain process in SMEs. IEEE 26th International Conference on Electronics, Electrical Engineering and Computing (INTERCON), Lima, Peru. 1–4. https://doi.org/10.1109/INTERCON.2019.8853634

Batini, C., Cappiello, C., Francalanci, C., & Maurino, A. (2009). Methodologies for data quality assessment and improvement. *ACM Computing Surveys (CSUR)*, *41*(3), 1–52. https://doi.org/10.1145/1541880.1541883

Benbasat, I., Goldstein, D.K., & Mead, M. (1987). The case research strategy in studies of information systems. *MIS Quarterly*, *11*(3), 369–386. https://doi.org/10.2307/248684

Benfeldt, O., Persson, J.S., & Madsen, S. (2020). Data governance as a collective action problem. *Information Systems Frontiers*, *22*(2), 299–313. https://doi.org/10.1007/s10796-019-09923-z

Benfeldt Nielsen O. (2017). A comprehensive review of data governance literature. *Selected Papers of the IRIS*, 8. Halden, Norway, August 6-9. 120–133.

Brous, P., Janssen, M., & Krans, R. (2020). Data governance as success factor for data science. *Responsible Design, Implementation and Use of Information and Communication Technology*, *12066*, 431.

Chakravorty, R. (2020). Common challenges of data governance. *Journal of Securities Operations & Custody*, *13*(1), 23–43. https://doi.org/10.69554/GAKU4007

DAMA International. (2017). DAMA-DMBOK: Data management body of knowledge. In Henderson, D., Early, S., & Sebastian-Coleman, L. (Eds.), (2nd ed). Technics Publications.

Easton, G. (2010). Critical realism in case study research. *Industrial Marketing Management*, *39*(1), 118–128. https://doi.org/10.1016/j.indmarman.2008.06.004

Eisenhardt, K.M., & Graebner, M.E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal*, *50*(1), 25–32. https://doi.org/10.5465/amj.2007.24160888

Eybers, S., & Setsabi, N. (2021). Responsible data sharing in the digital economy: Big data governance adoption in bancassurance. In S. Smys, V. E. Balas, & R. Palanisamy (Eds.), *Inventive computation and information technologies* (pp. 379–394). Springer.

Fletcher, A.J. (2017). Applying critical realism in qualitative research: Methodology meets method. *International Journal of Social Research Methodology*, *20*(2), 181–194. https://doi.org/10.1080/13645579.2016.1144401

Galliers, R.D., & Land, F.F. (1987). Choosing appropriate information systems research methodologies. *Communications of the ACM*, *30*(11), 901–902. https://doi.org/10.1145/32206.315753

Gegenhuber, T., Mair, J., Lührsen, R., & Thäter, L. (2023). Orchestrating distributed data governance in open social innovation. *Information and Organization*, *33*(1), 100453. https://doi.org/10.1016/j.infoandorg.2023.100453

Karkoskova, S. (2023). Data governance model to enhance data quality in financial institutions. *Information Systems Management*, *40*(1), 90–110. https://doi.org/10.1080/10580530.2022.2042628

Khatri, V., & Brown, C. (2010). Designing data governance. *Communications of the ACM*, *53*(1), 148–152. https://doi.org/10.1145/1629175.1629210

Lee, S.U., Zhu, L.M., & Jeffery, R. (2019, January 8-11). Data governance decisions for platform ecosystems. 52nd Hawaii International Conference on System Sciences (HICSS), Grand Wailea, HI, USA. 6377–6386.

Levinthal, D., & Rerup, C. (2006). Crossing an apparent chasm: Bridging mindful and less-mindful perspectives on organizational learning. *Organization Science*, *17*(4), 502–513. https://doi.org/10.1287/orsc.1060.0197

Lis, D., & Otto, B. (2020, August 13-15). Data governance in data ecosystems-insights from organizations. In *Americas Conference on Information Systems ACMIS*, Salt Lake City, UT, USA. AIS. https://aisel.aisnet.org/amcis2020/strategic_uses_it/strategic_uses_it/12

Maren. G. (2024, July 29). *Understanding the potential failures of a data governance program*. DataVersity. Retrieved May 19, 2025, from https://www.dataversity.net/understanding-the-potential-failures-of-a-data-governance-program

McAvoy, J., & Butler, T. (2018). A critical realist method for applied business research. *Journal of Critical Realism*, *17*(2), 160–175. https://doi.org/10.1080/14767430.2018.1455477

McAvoy, J., Nagle, T., & Sammon, D. (2013). Using mindfulness to examine ISD agility. *Information Systems Journal*, *23*(2), 155–172. https://doi.org/10.1111/j.1365-2575.2012.00405.x

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2020). The role of information governance in big data analytics driven innovation. *Information & Management*. *57*(7). https://doi.org/10.1016/j.im.2020.103361

Mu, E., & Butler, B.S. (2009). The assessment of organizational mindfulness processes for the effective assimilation of IT innovations. *Journal of Decision Systems*, *18*(1), 27–51. https://doi.org/10.3166/jds.18.27-51

Nielsen, O.B., Persson, J.S., & Madsen, S. (2018, June 25). Why governing data is difficult: Findings from Danish local government. In *International Working Conference on Transfer and Diffusion of IT*. Portsmouth, UK. (pp. 15–29). Springer. https://doi.org/10.1007/978-3-030-04315-5_2

Otto, B. (2011a, June 9-11). A morphology of the organisation of data governance. European Conference on Information Systems (ECIS) 2011, Helsinki, Finland.

Otto, B. (2011b). Data governance. *Business & Information Systems Engineering*, *3*(4), 241–244. https://doi.org/10.1007/s12599-011-0162-8

Otto, B. (2011c). Organizing data governance: Findings from the telecommunications industry and consequences for large service providers. *Communications of the Association for Information Systems*, *29*(1), 3. https://doi.org/10.17705/1CAIS.02903

Pan, S.L., & Pee, L.G. (2020). Usable, in-use, and useful research: A 3U framework for demonstrating practice impact. *Information Systems Journal*, *30*(2), 403–426. https://doi.org/10.1111/isj.12274

Panian, Z. (2010). Some practical experiences in data governance. *World Academy of Science, Engineering and Technology Management*, *62*(1), 939–946.

Parmiggiani, E., & Grisot, M. (2020). Data curation as governance practice. *Scandinavian Journal of Information Systems*, *32*(1), 3–38.

Redman, T.C. (2025, January 22). Data governance is failing-here's why. Chief Data Officer Magazine. https://www.cdomagazine.tech/opinion-analysis/data-governance-is-failing-heres-why

Rosemann, M., & Vessey, I. (2008). Toward improving the relevance of information systems research to practice: the role of applicability checks. *MIS Quarterly*, *22*(1), 1–22. https://doi.org/10.2307/25148826

Runde, J. (1998). Assessing causal economic explanations. *Oxford Economic Papers*, *50*(2), 151–172. https://doi.org/10.1093/oxfordjournals.oep.a028639

Schon, D.A. (1983). *The reflective practitioner how professionals think in action*. Basic Books.

Seidel, S., & Watson, R.T. (2014). Improving the societal effectiveness of IS research: The pursuit of prescriptive accuracy. Available at SSRN 2477917. https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=2477917

Swanson, E.B., & Ramiller, N.C. (2004). Innovating mindfully with information technology. *MIS Quarterly*, *28*(4), 553–583. https://doi.org/10.2307/25148655

Tallon, P.P., Short, J.E., & Harkins, M.W. (2013). The evolution of information governance at Intel. *MIS Quarterly Executive*, *12*(4), 189–198.

Vial, G. (2023). Data governance and digital innovation: A translational account of practitioner issues for IS research. *Information and Organization*, *33*(1), 100450. https://doi.org/10.1016/j.infoandorg.2023.100450

Walsh, J., & Ungson, G. (1991). Organizational memory. *Academy of Management Review*, *16*(1), 57–91. https://doi.org/10.2307/258607

Walsh, M.J., McAvoy, J., & Sammon, D. (2025). The data governance journey in practice: Insights from case study research. *Information Systems Management*, *42*(3), 471–488. https://doi.org/10.1080/10580530.2025.2477459

Weber, K., Otto, B., & Österle, H. (2009). One size does not fit all-a contingency approach to data governance. *Journal of Data and Information Quality(JDIQ)*, *1*(1), 1–27. https://doi.org/10.1145/1515693.1515696

Weick, K.E., & Sutcliffe, K.M. (2006). Mindfulness and the quality of organizational attention. *Organization Science*, *17*(4), 514–524. https://doi.org/10.1287/orsc.1060.0196

Weick, K.E., Sutcliffe, K.M., & Obstfeld, D. (1999). Organizing for high reliability: Processes of collective mindfulness. *Research in Organizational Behavior*, *21*, 81–123.

Wiener, M., Saunders, C., Chatterjee, S., Dennis, A.R., Gregor, S., Mähring, M., & Mertens, P. (2018). Information systems research: Making an impact in a publish-or-perish world. *Communications of the Association for Information Systems*, *43*(1), 466–481. https://doi.org/10.17705/1CAIS.04326

Williams, C.K., & Wynn, D.E., Jr. (2018). A critical realist script for creative theorising in information systems. *European Journal of Information Systems*, *27*(3), 315–325. https://doi.org/10.1080/0960085X.2018.1435231

Wolfswinkel, J.F., Furtmueller, E., & Wilderom, C.P. (2013). Using grounded theory as a method for rigorously reviewing literature. *European Journal of Information Systems*, *22*(1), 45–55. https://doi.org/10.1057/ejis.2011.51

Wynn, D.E., Jr., & Williams, C.K. (2012). Principles for conducting critical realist case study research in information systems. *MIS Quarterly*, *36*(3), 787–810. https://doi.org/10.2307/41703481

Yebenes, J., & Zorrilla, M. (2019). Towards a data governance framework for third generation platforms. *Procedia Computer Science*, *151*, 614–621. https://doi.org/10.1016/j.procs.2019.04.082

Appendix 1 – Mindless Data Behaviours in UniOne

Table A1. The mindless data behaviours in UniOne.

Data Access	
Sensitivity to Operations	**Commitment to Resilience**
Users circumvent restrictive data access policies to get the job done	Lots of time wasted using spreadsheets to combine data from operational reports
Devolved DG results in inconsistent data access policies across departments	Lack of self-service data access options for strategic data generating extra workload
Data Quality	
Sensitivity to Operations	**Commitment to Resilience**
Poor version control leading to differing versions of data sets wrongly classed as poor data quality	Poor master data quality hampering systems integration
Genuine data quality problems missed because of poor data literacy	Time spent validating data instead of correcting the root cause of quality issues
Data quality can used as an excuse to put off making decisions	
Data Principles	
Sensitivity to Operations	**Commitment to Resilience**
There is a lack of focus on long-term planning	No complete view of the *customer*, it must be constructed manually from multiple operational systems
The lack of a DG policy to deal with exceptions allows obstructive users to employ the quality argument to prevent progress	Many data tasks are manual and time consuming
There is no mechanism to learn from the problems they encounter.	DG principles have evolved in departments and are not co-ordinated or regularly reviewed
Devolved data ownership model which is based largely on GDPR policy at centre of many issues	No forum to collate organisation wide data needs.