

## Revealing the Root Causes of Digital Health Data Quality Issues: A Qualitative Investigation of the Odigos framework

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### Abstract

*Digital health data quality (DQ) is a critical concern in the healthcare industry, jeopardizing the secondary use of data for transforming population health, and hindering patient care and organizational outcomes. Limited evidence exists for explaining why these DQ issues emerge. The Odigos framework is a notable exception asserting that DQ issues emerge from three worlds: material (e.g., technology), personal (e.g., technology users), and social (e.g., organizations/institutions) but has yet to unpack the elements within these worlds. Through deductive and inductive analysis of interview data from a case study of the Emergency Department of Australia's first large digital hospital, we apply and extend the Odigos framework by identifying elements emanating from the three worlds and their interrelationships as root causes of DQ issues. These elements can then be used by hospitals to develop strategies to proactively improve their digital health DQ.*

**Keywords:** Digital health, data quality, Odigos framework, root cause analysis, case study.

### 1. Introduction

Digital health, defined as “the use of digital technologies for health, encompassing eHealth, mHealth, and emerging technologies” (Troncoso & Breads, 2021, p. 504), has long been proffered to improve the efficiency, effectiveness, and equitable patient care delivered by a productive and engaged workforce (Fichman et al., 2011; Hansen & Baroody, 2020; Kaplan, 1995). This digital health ideology is

collectively shared by governments globally, private and public healthcare organizations, frontline clinicians, and healthcare consumers (World Health Organization, 2021). The foundations of this ideology are deep rooted in technology determinism (Kaplan, 1995), yet in practice digital health has been associated with ambiguous outcomes (Hansen & Baroody, 2020)

The promise of digital health is largely due to the ability to electronically collect administrative and clinical data, which can be analyzed to improve decision making at multiple levels (Reisman, 2017). One challenge in meaningfully harnessing this data is the quality of the data captured in digital health systems. It is widely acknowledged that digital health systems have “led to the recording of a greater quantity of bad data instead of improving the quality of data” (Darko-Yawson & Ellingsen, 2016, p. 243). Such data quality (DQ) errors may hinder patient safety (Wang et al., 2019), clinician productivity (Wiebe et al., 2020), and research (von Lucadou et al., 2019).

It is imperative to understand the root causes of digital health DQ issues given their potential for detrimental impacts. Despite typologies classifying DQ issues in healthcare (Kahn et al., 2016; Weiskopf et al., 2017), limited work has focused on explaining *why* these issues occur. The Odigos framework is a notable exception, which instantiates semiotics theory in the context of process-oriented DQ. The Odigos framework posits that process-oriented DQ issues stem from the social (e.g., situational and macro level, structures and norms), material (e.g., technology and infrastructure), and personal worlds (e.g., system users, analysts) (Andrews et al., 2022). Although the Odigos framework was designed to provide insights into process-oriented DQ issues, we argue that it is

commensurate with the broader context of DQ in digital health as process-oriented data is a subset of data extracted from electronic medical records, which records the patient's journey. The Odigos framework provides initial insights into the root causes of DQ issues. These insights, however, have largely been based on expert-opinion rather than garnered from the coalface of an organization.

We seek to identify the root causes of digital health DQ issues in a hospital setting recognizing the experience and perceptions of front-line, managerial, and technical staff. We focus on hospital settings because: 1) hospitals have recently undergone digital transformations (Eden et al., 2019b); and 2) healthcare delivery in hospitals requires multidisciplinary teams, heightening the potential for and consequences of DQ issues (Munoz-Gama et al., 2022). Guided by the research question - why do digital health DQ issues occur in hospital settings? - our interdisciplinary team of healthcare professionals, digital health and DQ experts performed a case study of the DQ issues in the emergency department of a large digital hospital.

## 2. Theoretical Background

### 2.1. Digital Health Data Quality

Despite the importance of data quality (DQ) being recognized across multiple fields, there is little consensus surrounding what constitutes DQ (van Hove et al., 2017). Consistent among these definitions is the complex nature of DQ and the need for it to be decomposed into dimensions (Landis-Lewis et al., 2015). Although, depending on the DQ framework employed different dimensions exist. For instance, Wang and Strong (1996) consider four DQ dimensions: intrinsic, contextual, representational, and accessibility; Weiskopf et al. (2017) identifies three dimensions: completeness, correctness, and currency of data; Makeleni and Cilliers (2021) considers six dimensions: completeness, consistency, conformity, accuracy, integrity, and timeliness.

To derive a consolidated set of digital health DQ dimensions, we reviewed 227 digital health DQ articles and extracted the DQ dimensions from the articles. We constantly compared the DQ dimensions together examining their similarities and differences, which resulted in a finalized set of six dimensions, which were independently verified by DQ experts. As a result, we view digital health DQ as the extent to which the data is accurate, accessible, complete, consistent, contextually valid, and current.

Accuracy refers to “the degree to which data reveal the truth about the event being described” (Makeleni & Cilliers, 2021, p. 4). When examining

accuracy, scholars describe: correctness of data in communicating parameters (Afshar et al., 2021); conformance of data with structural and syntactical rules (Kahn et al., 2016); and, plausibility of data (Lee et al., 2017).

Accessibility refers to the extent to which it is feasible “for users to extract the data of interest” (Weiskopf et al., 2017, p. 4). Literature concurs that digital health facilitates accessibility with the ability for data to be accessed anywhere at any time, overcoming physical and temporal boundaries (Top et al., 2012). Although, from a secondary use of data perspective accessibility concerns are still present as the data may be available but not in a structured format making it difficult to extract (Dentler et al., 2014).

Completeness refers to “the absence of data at a single moment over time or when measured at multiple moments over time, without reference to its structure or plausibility” (Estiri et al., 2018, p. 18). In examining completeness, scholars refer to whether the documentation describes the whole truth about a patient's medical history (Jetley & Zhang, 2019). Others describe that missing and fragmented data hinders completeness (McCormack & Ash, 2012).

Consistency refers to the “absence of differences between data items representing the same objects based on specific information requirements. Consistent data contain the same data values when compared between different databases” (Makeleni & Cilliers, 2021, p. 5). Capturing consistent data is difficult in health settings due to the manual nature of the process which involves multiple teams and goals (Garg et al., 2014).

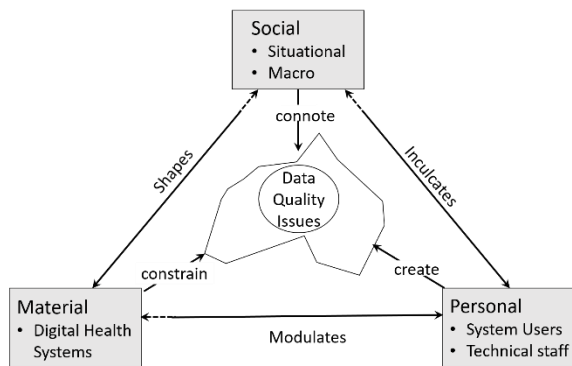
Contextual validity described as ‘fitness of use’ (Richesson et al., 2013) refers to DQ being “dependent on the task at hand” (Weiskopf et al., 2017, p. 4). Literature suggests the need to deeply understanding the technical, organizational, behavioral, and environmental context which gives rise to data (Daniel et al., 2019). Granularity of data has a bearing on whether data is fit for use (von Lucadou et al., 2019).

Currency is “the degree to which data represent reality from the required point in time” (Afshar et al., 2021, p. 2). Digital health data should be current, accessible, and reflect the profile of the patient at the time of data access (Chiasera et al., 2011). This requires events to be recorded representative of the clinically relevant time (Lee et al., 2017).

### 2.2. Odigos framework

We employ the Odigos framework (Figure 1) to understand the root causes of digital health data quality (DQ) issues. The Odigos framework has been cumulatively developed to prognostically and

diagnostically identify why DQ issues occur (Andrews et al., 2020, 2022; Emamjome et al., 2020). The Odigos framework builds on Mingers and Willcocks (2017, pp. 19, 21) semiotics framework, which asserts that semiosis (content created through the combination of signs and symbols with inherent meaning) occurs through the interactions of three worlds, the: 1) Personal world which represents “individuals generating communication in line with their conscious (and unconscious) intentions”; 2) Social world which consists of macro and situational “norms, practices, and roles”; and 3) Material world which is the “medium through which communications can occur”, including technology artifacts.



**Figure 1. Odigos framework adapted from Andrews et al. (2022)**

According to Mingers and Willcocks (2017, p. 17), semiosis “seeks to look behind or underneath the manifest appearance of texts to reveal the underlying social and cultural structures that generate them”. In the Odigos framework, Andrews et al. (2022) examine the DQ of the content of event logs extracted from technology artifacts as a form of semiosis. We assert that digital health data is indicative of semiosis as it is generated by digital health systems (i.e., material world) for healthcare professionals who hold their own beliefs, experiences, and motivations (i.e., personal world) in a healthcare setting that is underpinned by culture, policies, and norms within a broader institutional environment (i.e., social world).

In developing the Odigos framework, Emamjome et al. (2020) provide an example of the root causes of DQ issues related to national emergency access targets based on an Auditor General Report. The authors speculate that the root causes for the DQ issues stem from the: 1) social world including financial incentives (macro level), and key performance indicators (situational level); 2) material world with the digital health system configured to segment the emergency department from the short-stay unit; and, 3) personal world with staff feeling pressured to meet targets. While providing insights into root causes, empirical

analysis within the site was not performed. The Odigos framework was later validated by process mining experts (Andrews et al., 2020) and applied to speculate the root causes of DQ errors present in event log imperfection patterns (Andrews et al., 2022). While these studies represent much needed first steps into the development of a comprehensive framework for analyzing the root causes of DQ issues, they are largely from an etic rather than an emic perspective.

### 3. Method

We draw on an in-depth single case study methodology, which allows for exploration of empirical phenomena in its natural setting (Lee, 1989).

#### 3.1. Case Study Setting

We examine the root causes of digital health data quality (DQ) issues within the emergency department (ED) of a large digital hospital in Australia. The hospital is publicly funded with over 65,000 presentations to ED annually. The hospital went live with an ieMR (integrated electronic medical record) in two phases: in 2015 they implemented an electronic medical record system and computerized provider order entry, followed in 2017 by the integration of clinical decision support, ePrescribing, and research functionalities. The ieMR has a single database instance and is used by multiple hospitals in the State, posing challenges related to standardization, but large opportunities for improving clinical practice at scale. As a result of using the ieMR, the hospital has experienced benefits related to improving the efficiency and effectiveness of care, however DQ remains a challenge. In addition to the ieMR, the ED relies on other digital systems (e.g., hospital-based corporate information system for administration purposes, consumer integrated mental health and addiction system for mental health patients), some of which are integrated whilst others possess interoperability challenges.

The ED provides a compelling case because it is: 1) the most measured and data-driven area of the hospital; 2) serves as the initial contact point between a hospital and a patient; 3) deals with a diverse range of patients’; and, 4) involves the transfer of patients to other wards. As such, any DQ issues in the ED have the potential to be perpetuated hospital-wide.

#### 3.2. Interview Data Collection and Analysis

We relied on semi-structured interviews (Appendix 1) coupled with archival data and

observations. Purposive sampling (Saldaña, 2021) was used to identify participants from multiple roles as each cohort interacts with the ieMR in multiple ways and contribute to and experience DQ issues differently. For instance, technical staff typically resolve DQ issues, clinical and administrative staff create and experience DQ issues in their front-line work, whereas clinical managers and clinical researchers are impacted by DQ issues when they perform data analysis and decision making tasks. The interviews were scoped to *issues* associated with DQ so areas for improvement could be identified. 21 people (table 1) participated, with each interview lasting approximately 40 minutes. Theoretical saturation was reached with no new DQ themes or impacts emerging. Interviews were recorded, transcribed, and uploaded to NVivo for analysis.

**Table 1. Interview Participants**

Role of Interviewees	Count	Identifier
Technical	4	T1-T4
Clinical and Admin. Staff	12	C1-C12
Strategic Clinical Managers	3	M1-M3
Clinical Research	2	R1-R2
Total	21	

To analyze the interviews deductive and inductive coding was used. We first employed deductive coding in two ways: 1) the consolidated set of DQ dimensions (as outlined in the Theoretical Background) was used as a classification framework to deductively classify the DQ issues that were experienced by interview participants; and 2) the Odigos Framework – material, personal, and social world – was used as a high level classification framework to deductively classify the root causes of DQ issues that were expressed by interview participants.

When deductively classifying the root causes into the Odigos framework, the three worlds served as aggregate dimensions, and excerpts of interview data were recorded as first order concepts (e.g., standardized fields, structured fields, free-text fields, codified fields etc.) underneath the aggregate dimension. Through inductive analysis (Saldaña, 2021) we constantly compared each of the first order concepts to identify the root causes of DQ themes (e.g., guided data entry) within each aggregate dimension (i.e., material world). This resulted in the material world being formed of five themes; the personal world being formed of three themes; and the social world being formed of two high level themes with their own dimensions.

For DQ impacts, an inductive approach was also used where the first order concepts related to impacts were first coded and then constantly compared to each

other to identify impact themes. In total, four impact themes were identified. After deductively analyzing the DQ dimensions and inductively analyzing both the root causes and impacts of DQ, we proceeded to theoretical coding to identify the relationships: 1) between the worlds; and, 2) between DQ issues and DQ impacts. This was supported by creating individual visualization maps within NVivo.

The analysis was undertaken by three independent coders who ongoingly managed a coding rule book in nVivo (with descriptions recorded under each node). The coders reconvened at multiple times to discuss their coding and to ensure a consistent approach was followed. Coder corroboration was also performed with two of the coders independently verifying all codes/ relationships and discussing any uncertainties until consensus was reached (Saldaña, 2021).

## 4. Findings: Root Cause Analysis of Data Quality Issues

Below, we provide a summary of the digital health data quality (DQ) issues and their impacts that emerged in ED followed by insights into the three worlds and their relationships that shape DQ.

### 4.1. Digital Health Data Quality Issues

Participants discussed all six DQ dimensions to varying degrees and varying extent of severity. Accuracy, completeness, and consistency were the most saliently discussed dimensions.

Positive sentiment existed for data accuracy with a participant indicating “90% of the time, [the data is] very good, usually accurate, and [provides] a very good guide” (C1), although staff primarily reported that “accuracy is definitely an issue out there” (T1). The issue with accuracy spanned multiple tasks including clinical documentation, diagnostic coding, prescription errors, and selection of inappropriate identifiers. As an example, a clinician described challenges with perpetual inaccuracies resulting from users copying and pasting clinical notes, “People will copy the same notes day in day out ...and [when] there’s an error, it just compounds the error.” (C2)

In contrast to data accuracy, participants viewed completeness more favorably with an executive noting “the ieMR gives us so much more information than we have ever had before. ...That’s a huge advantage” (M1). Yet, the data is largely “sitting there untapped” (M1). Despite improved completeness when compared with the paper charts of the past, there is still a large amount of missing data: “if [the] problem list [is] entered [it provides the patient’s] comorbidities,

which is helpful. ..But often that problem list is not there because most of the time the doctors free-type their [the patient's] past medical history." (C3)

The need for consistency in data was regularly raised. Participants discussed inconsistency in terms of how documentation was inputted into the iEMR, including the use of structured/unstructured notes, codified/non-codified fields and inconsistent naming conventions at local and state levels: "The amount of different variations, ...it gets out of control very quickly. It's actually quite complex." (T2). In some areas of ED, standardized documentation templates were created to minimize inconsistencies.

In contrast to accuracy, consistency, and completeness; issues involving accessibility, currency, and contextual validity were less common. Participants generally held favorable views regarding the accessibility and currency of data within the iEMR particularly secure remote access to "use the iEMR from home" (C2) with "real time ...information at your fingertips... [providing] a very good picture of [the patient]" (M1).

Contextual validity shared similar issues with accuracy, consistency, and completeness, but was prevalent among certain patient cohorts, including mental health, radiology, and resuscitation. For instance, clinical notes for patients who are requiring resuscitation are generally unstructured and inconsistent due to the life and death stakes within the resuscitation area. Work is underway to create standardized templates in this area. For mental health patients, core steps of the patient triage process are often overlooked hindering the quality of process data. This occurs because mental health patients arriving at ED are quickly transferred to mental health areas within "five minutes of arrival" (T3). For patients who go to radiology, a defect resulting from a recent iEMR update resulted in patient data not being visible to ED.

## 4.2. DQ Impacts

We identified four types of DQ impacts: clinical, staff, business process, and organizational.

Staff often reported that DQ issues do not affect clinical outcomes; rather the issues tend to pertain to "administrative ...data that, even if its inputted wrong, it doesn't affect current practice on the floor" (C4). This is further corroborated by another participant who indicated that from a patient flow perspective, "[poor DQ is not an] immediate effect [rather] the patient will go wherever they have to go and get treated" (T3). Others highlighted that DQ issues cause confusion in the patient journey, delays in bed bookings, and delays to medication provisioning. The delays in medication provision largely results from unclear roles and

responsibilities between junior doctors and registrars, which has been an issue pre-dating the iEMR: "Who's responsible for charting the medications? ...ED junior doctors [or] medical registrars... it's not clear ...and one thinks the other should be doing it. ...So it falls through the cracks. ...It does cause [impacts because] then [the patients] are not getting their medicine, so we can't supply until we've got an order" (C3).

DQ issues resulting from data entry during the patient journey was a key frustration of clinical staff and often cited as placing undue burden on non-clinical staff. Clinical staff expressed frustration with perpetuating data entry issues with administrative and technical staff having to routinely fix data entry errors that occur during triage. Research staff also identified that inconsistency in documentation from multiple sources made it difficult to identify a source of truth, due to interoperability between systems, and data being recorded in different places and in different ways by healthcare professionals. "Sometimes you're trying to extract the mental health history in the iEMR and each [staff member] has a different list of mental health history for the patient" (R1).

Participants held largely mixed views on business process outcomes related to the efficiency of the care process. Some staff indicated that the iEMR results in data duplication efforts due to interoperability issues between systems leading to inefficiencies. Whereas other staff indicated that due to the accessibility and currency of information in the iEMR they were able to save time from "jumping around from program to program looking for all that information" (C2).

DQ issues were regularly cited as impacting the hospital such as resourcing, funding, and compliance. These issues include incomplete data entry with staff not selecting appropriate diagnostic codes, patient demographics, and inaccurate times entered during the patient journey. Others noted "there is a lot of stuff that doesn't quite fit, but the challenges are to stick to the legal guidelines" (C5) rather than forming "crazy work arounds" (C6). This resulted in extensive and ongoing data cleaning procedures. "We go through and clean the data. ...We have daily data cleans, weekly ones, and then also the monthly one to make sure we really capture everything we need to. And majority of the data is then utilized for our funding purposes" (T1).

## 4.2. Root Causes: Worlds

Below, we present our findings from the deductive and inductive analysis using the Odigos framework as a guide to identify the root causes of digital health DQ issues. Specifically, we are focused on examining the root causes resulting in negative rather than positive effects to DQ.

**4.2.1 Material World.** Participants discussed five themes within the material world that directly or indirectly (through influencing the personal/social world) impact DQ: usability, controls, infrastructure, fit-for-purpose, and guided data entry.

Usability, or lack thereof, was a core source of DQ errors. Participants lamented the user interface, its cluttered nature, meaningless icons, difficulty finding information, and multiple places to enter in the same piece of data. As a participant describes: *“The [ieMR] screen that the nurses use ...is very messy and has a lot of silly things ...[that] take up visual space.”* (C6)

Mixed perceptions regarding controls and alerts were reported. Some staff indicated that the ieMR required more *“rules and logic”* (T2) with limited controls surrounding timestamps *“sometimes the year changes to [a future time] and you don’t realize ... [that’s] happened* (C7). Others indicated that some built-in alerts are meaningless *“the pharmacist review icon ...just constantly comes up. ...Even when we reviewed a patient, we finished our history, ...we tick that off as pharmacist clinical review done and then it fires off again for the next day.”* (C3).

In terms of infrastructure, many described interoperability issues between systems particularly in pharmacy, radiology, and mental health. For instance, when ED patients returned from radiology, the patient encounter would disappear from the ED component of the ieMR providing an incomplete and inaccurate representation of the patient’s journey. *“There are a few glitches that are very frustrating, so patients, if they go outside of the ED for radiology ...they will disappear off the tracking list”* (C6).

Functionality and misfits were reported. This included misalignment between the ieMR’s diagnostic codes and Australian diagnostic codes. In addition, the way the nursing assessment was originally configured did not align with ED nurse practice. *“We found that what was the ED nurse assessment didn’t really fit how we wanted to do an initial nursing assessment. ...There was no consistency about what nurses were doing and which buttons they were clicking and what sort of documentation they were collecting or what data they were writing about.”* (T3).

The usability, controls, and fit-for-purpose themes were related to guided data entry, which describes structured approaches to documentation, including codified fields, templates, or conversely free text fields. Regarding codified fields, participants indicated that the meaning of the options within a field were challenging to understand. Staff indicated that free text fields promoted completeness and accuracy when compared to codified fields, as *“codified data needs to be put in properly and [takes more] time ...[than] just being able to write this patient has [this*

*condition]. We actually do it properly [in our free text notes]”* (C2).

**4.2.2 Personal World.** Root causes of DQ issues emanating from the personal world included user characteristics, user behavior, and patient behavior. User characteristics and user behavior were most prevalently discussed by participants.

In terms of user characteristics, participants indicated that staff’s ieMR knowledge, fear of the ieMR, domain expertise, and diligence impacted DQ. Participants reported a lack of awareness with how DQ errors impacted others downstream in the patient journey and resultant implications for organizational and policy levels. *“Because [staff are] not doing audits, ...they’re not worried about having to retrieve that data. ...The fact that they’ve cut and paste the previous medical history, or ...patient’s medications, and it’s not codified ...doesn’t worry them”* (C2).

In terms of user behavior, workarounds, resistance, and inattentive data entry impacted DQ. Workarounds included batch processing of data entry hindering currency; bypassing mandatory fields with *“[staff] just putting in a dot or space and that made the mandatory field go away”* (M2) impacting completeness and accuracy; and copying and pasting inaccurate clinical data. Some staff resisted structured form fields opting to insert documentation into free text fields. Inattentive data entry usually occurred in codified fields, with data *“constantly put in incorrectly”* (T3). Some user behavior positively impacted DQ such as data curators routinely cleaning the ieMR data.

Patient behavior could also negatively impact DQ. Some patients would tell doctors differing and contradictory details about their health, which was entered into the system. This made it challenging for healthcare professionals to identify the source of truth.

**4.2.3 Social World.** Root causes of DQ issues were observed at macro and situational levels. At the macro level, DQ issues were related to the statewide-healthcare system, funding structures, and legislation and accreditation bodies. While the statewide approach to the ieMR with the single database instance provides great potential to work *“as a great big network system ...where we don’t really need to work as ...separate hospitals and five separate EDs”* (M2), gaining statewide agreement on standardized approaches to data entry is challenging. *“For the last four years or so they’ve been working on a digital admission form, but because it has to get statewide approval, it’s gone back and forth about a bazillion times”* (C6). Funding structures and policies did not directly cause DQ issues although the resource

implications of poor DQ resulted in structures and roles being created to clean the data to make sure it was appropriate for state-level funding requirements.

Situational root causes including resource constraints, training, workforce dynamism, strategic intent, and culture were discussed by participants. Some of these root causes negatively impacted DQ, whereas others positively impacted DQ either directly or indirectly through impacting the personal world and the material world. Resource constraints with staff having a high workload negatively impacted DQ: “*Not enough, no people, not enough resourcing*” (C5).

Staff held mixed perceptions in terms of training. “*Everyone does training on how to use the ieMR*” (C1) but “*the ongoing training is a bit lacking ...[with] education gaps and people making the same mistakes over and over again*” (C7). The challenges regarding training stem from the dynamic nature of the ED workforce, with junior doctors undergoing rotations. The education gaps and resultant DQ issues has resulted in new/expanded workforce roles including: business process improvement officer, data validation officers, health informatics personnel, as well as partnerships with external subject matter experts.

At the executive level, strategies had been put into place to improve DQ issues: “*Consistency in the understanding at a clinical level and in terms of the use of that data is so low*” (M2). This involved improving consistency in documentation and data definitions. To improve documentation a group of nurses worked on a project to identify a consistent approach to nursing documentation.

The importance of DQ was ingrained into the management culture. “*Our executive have a fantastic understanding of the data and they're able to use it in a way to prove ...what we need and what we've been saying*” (C6). Yet, in some cases, professional cultures proved detrimental to DQ, with some administrative staff feeling they were held accountable and responsible for fixing DQ issues made by clinicians.

**4.2.4 Relationships between worlds.** DQ issues can also result from the complex web of interrelated worlds, whereby the personal world, social world, and material world all shape each other. In our case, we identified the: 1) social world inculcating the personal world, 2) personal world inculcating the social world; 3) material world modulating the personal world; and 4) social world shaping the material world.

The social world inculcated the personal worlds in several ways, through educating users, empowering clinical judgement, facilitating research, culture inhibiting data entry, creating roles, and burdening the workforce. For instance, to improve DQ, the data curator generates monthly reports to identify where

DQ issues are occurring and to feed that back to the responsible teams in an effort to improve how staff are using the ieMR. “*We do monthly reports to the nursing education team to try and improve the DQ around the triage nurses.*” (T3).

The personal world inculcated the social world through hampering strategic change. Due to user behavior causing detrimental impacts to DQ, strategic focused data curator roles largely ended up being operational in nature burdened by data cleaning. “*We're so focused on fixing the mistakes, we were never nipping it in the bud. And that was quite annoying because in [this] role, you can make heaps of strategic changes and [make] the system a lot better for everyone. Yet, they're bogged down on just changing errors over and over again.*” (C7)

The material world modulated the personal world through: promoting standardized data entry, mandating data entry, allowing flexible data entry, working around system deficiencies, and requiring manual processes. Promoting standardized data entry through templates, form-fields, codified fields in a non-mandated manner shaped user behavior in some instances to improve data completeness. “*For junior doctors and registrars it's pretty standardized. They have admission templates as well, [which] are thorough and [they] do a really good job at listing things.*” (C6). In other instances, they were bypassed with inaccurate data entered requiring data cleaning.

The social world also shapes the material world by constraining access rights; enforcing procedures, introducing standards, generalizing fit for purpose changes, updating to meet external changes, and developing features. For example, the nursing template that was initially in the ieMR was not fit-for-purpose, as a result the executive team organized for a team of ED nurses to develop a standardized template for documentation that was aligned with their practice. While this example shows the relationship between the social and the material world, this template was then used by nursing staff, implicating the personal world and improved DQ. As this example shows all three worlds can shape each other to ultimately effect DQ.

## 5. Discussion

As illustrated in Figure 2, in demonstrating the applicability of the Odigos framework for detecting the root causes of digital health data quality (DQ) issues, we extend the framework by 1) evidencing six types of DQ: accuracy, accessibility, completeness, consistency, contextual validity, and currency; 2) synthesizing four impacts: clinical, staff, business processes, and organizational; 3) unpacking the root causes of DQ issues within each world; and 4)

providing insights into the mechanisms underpinning the interactions between each world.

By revealing the root causes, it became evident that they were related to established streams of literature: organization-enterprise systems fit theory, theory of effective use, institutional theory, and business value of IT. These theories have largely been examined in isolation without coalescing around the concept of DQ. Together they provide complementary and actionable strategies to hospital executives to proactively improve the DQ issues experienced.

For the material world, the theory of organization-enterprise systems fit (Strong & Volkoff, 2010) may provide remedies for resolving the root causes. This is because the material world root causes resemble the misfits present in the theory. The theory suggests that issues arise from the structure of the system and the structures that emerge from using the system, with attention needed to improve alignment whether that be through the vendors' development of features or the organization as they tailor their solution.

For the personal world, user characteristics, user behavior, and patient behavior influence DQ implicating two pillars of information systems research: user characteristics and system use. Particularly, the theory of effective use (Burton-Jones & Grange, 2013) could provide insights, as it indicates the learning and adaptation necessary for users to transparently interact with the system, determine the fallibility of representations, and make informed decisions based on the data present in the system.

For the social world, we identified factors at macro and situational levels. At the macro level, we witnessed the effect of the statewide system, legislation, and policy. The concept of institutional work can provide insights into the actions of organizational actors to overcome institutional constraints (Lawrence & Suddaby, 2006). For the situational factors, resource constraints, training, workforce dynamism, and culture played an important role. This could be explained through examining the business value of IT—specifically organizational complementary resources (Melville et al., 2004).

Consistent with the Odigos framework, we identified that the social world shapes the material world and inculcates the personal world, and the material world modulates the personal world. We further identify *how* this occurs. The social world shapes the material world through constraining access rights; enforcing procedures, introducing standards, generalizing fit for purpose changes, updating to meet external changes, and developing additional features. Whereas the social world shapes the personal world through educating users, empowering clinical judgement, facilitating research, culture inhibiting

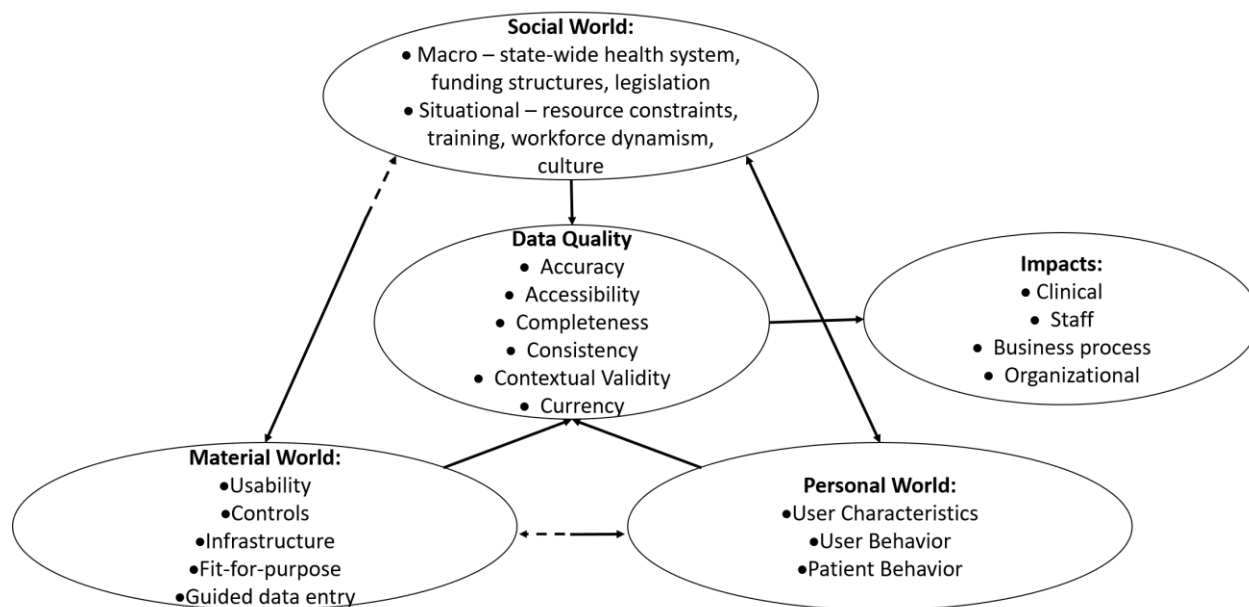
data entry, creating roles, and burdening the workload. Finally, the material world modulates the personal world through promoting standardized data entry, mandating data entry, allowing flexible data entry, working around system deficiencies, and requiring manual processes. Extending the Odigos framework, we observed examples where the personal world inculcated the social world through constraining change. Similar to the Odigos framework, we did not witness the material world shaping the social world, or the personal world modulating the material world although we argue that they are theoretically plausible. For instance, when digitally transforming, the material world impacts the social world requiring workforce transformation (Eden et al., 2019a). Likewise, enhanced use behaviors could collectively shape the material system (Bagayogo et al., 2014).

## 6. Conclusion

This research represents the first empirical study grounded in the perceptions and experiences of frontline, managerial, and technical staff to demonstrate the utility of and extension of the Odigos framework. We evidence the complete chain of the root causes of data quality (DQ) issues emanating from each world and the mechanism underpinning the relationships between the worlds, through to the taxonomy of six DQ dimensions, through to the impacts generated. Practically, this research provides insights to healthcare stakeholders of where DQ issues are emanating from so that targeted strategies can be identified and performed. Future research should extend this work through developing a portfolio of recommendations that hospital executives can follow to proactively improve DQ issues based on the root causes identified in this work.

Although, our research design provided the potential to gather in-depth insights into why DQ issues occur and their impacts, limitations exist in the ability of our findings to be generalized across settings due to a single exemplar case study being performed. We believe the root causes of DQ issues and their impacts could well differ across settings and should be inductively identified, although we tentatively anticipate the approach we have followed - in terms of drawing on DQ dimensions and Odigos framework as they are grounded in literature and theory - may be generally applicable (Lee & Baskerville, 2003) to other conceptually similar environments. We call for future research to apply the Odigos framework in other settings to provide insights into the generalizability of the Odigos framework across settings. In addition, future research should also triangulate these findings with system logs to objectively identify DQ patterns.





**Figure 2. The Root Cause Analysis of Digital Health Data Quality Issues**

## 7. Appendix 1: Interview Questions

The interviews were tailored to each role with questions pertaining to DQ issues experienced, DQ impacts, and facilitators/impediments of DQ. Below, we provide a *sample* of the interview guide. For the complete interview guide, please email the first author. 1) Can you describe the typical data driven decisions that you make in your role? 2) What challenges exist when acting on data? 3) How do you describe the quality of data? 4) How does the quality of the data you are drawing on impact your decisions? 5) What do you believe are the reasons behind the DQ issues?

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