Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

A MATURITY MODEL FOR DIGITAL TWINS IN HEALTHCARE

Navonil Mustafee[1], Alison Harper[1], Joe Viana[2], and Thomas Monks[3]

[1]Centre for Simulation, Analytics, & Modeling, University of Exeter Business School, Exeter, UK
[2]Industrial Econ & Tech. Mgmt, Norwegian University of Science & Technology, Trondheim, NORWAY
[3]Health and Community Sciences, University of Exeter Medical School, Exeter, UK

ABSTRACT

Digital models, digital shadows, and digital twins (DTs) are increasingly used in manufacturing/Industry 4.0 to represent levels of integration between physical systems and their digital counterparts; data-flow mechanisms are the enablers of such integration. Healthcare operations management has also witnessed rising interest in hybrid models that use real-time data to increase situational awareness (SA) and enable short-term decision-making. In M&S literature, such models are referred to as Real-time Simulations (RtS) and DTs. Healthcare organizations can realize a heightened state of SA by transitioning from conventional modeling to RtS/DTs. The paper presents a Maturity Model for DTs to contextualize the increasing levels of healthcare Information Systems/Information Technology (IS/IT) integration with real-time models that such a shift will necessitate. The higher the Maturity Level of IS/IT integration, the greater the opportunity to develop modeling artifacts that realize the potential of real-time data and enable organizations to attain higher levels of SA.

1 INTRODUCTION

In IT management, maturity models enable the objective assessment of the IT capabilities of an organization against its goals, external requirements, and benchmarks, which help identify opportunities for new capabilities and solutions in a continual improvement cycle (Becker et al. 2009). The improvement cycle usually consists of a sequence of discrete maturity levels representing an evolutionary path from an existing state to a future anticipated state (*ibid.*). A five-point Likert scale is the most popular way of evaluating maturity, with '5' representing the highest maturity level (De Bruin et al. 2005).

The Software Engineering Institute (SEI) at Carnegie Mellon University developed the first Capability Maturity Model (CMM) in the late 1980's. The foundation of the SEI CMM was the concepts of effective processes developed by Philip Corsby, Edwards Deming, Joseph Juran and other pioneers of quality management (SEI 2010). Maturity models have since been developed for application areas such as business process improvement (Röglinger et al. 2012), project management (Fabbro and Tonchia 2021), and IS (Lasrado et al. 2015). Fraser et al. (2002) present examples of maturity models from a range of subject areas, identifying the discrete stages or maturity levels associated with the models (e.g., Level 1-5, Level A-F, Stage 0-3).

This paper focuses on maturity models for digital twins (DTs) in healthcare. DTs represent the highest level of maturity as, arguably, they represent the current state-of-the-art in real-time Modeling & Simulation (M&S). However, several evolutionary paths exist in progressing from minimal modeling capability to total maturity. In previous work, we presented the distinction between Real-time Simulation (RtS) and DTs that are developed from an Operations Research/Management Science (OR/MS) perspective (Mustafee, Harper, and Viana 2023a; Mustafee, Harper, and Viana 2023b). We argued that the two core requirements for an OR/MS RtS/DT are real-time data availability and a computational model for experimentation. We identified that the transition from a conventional OR/MS simulation, e.g., a discrete-event or agent-based simulation reliant on historical data, to a fully-fledged DTs (this requires high levels of integration with sources of real-time data) includes an intermediate stage, which we define as RtS. The RtS computational models complement (predominantly) historical data with limited real-time feeds *(ibid.)*. This paper advances the discourse on conventional modeling, RtS and DTs by investigating maturity models through the lens of IS and IT. The IS/IT perspective is important since it is core to data acquisition. As healthcare organizations evolve from a basic level of IS/IT capability to full maturity, the IS/IT systems support the development of increasingly complex models and act as enablers for real-time RtS/DT experimentation, enhancing organizational *situational awareness*, a knowledge state that is considered to be essential for decision-making and performance in dynamic environments (Harper, Mustafee, and Pitt 2023).

The remainder of the paper is organized as follows. Section 2 presents our contribution to the literature on hybrid modeling and discusses Kritzinger et al. (2018) classification of digital models in relation to RtS and OR/MS DTs. Section 3 reviews the literature on maturity models for DTs. Section 4 is on the case study motivating the development of the IS/IT maturity model. Section 5 uses Unified Modeling Language (UML) notation, which is a visual modeling language frequently employed in IS/IT for the design of software artifacts, to discuss the increasing levels of system integration, which serve as the building blocks for the *maturity model of IS/IT system integration for DTs in healthcare* (Section 6). Section 7 discusses the generalisability of the maturity model and concludes the paper.

2 HYBRID MODELS USING REAL-TIME DATA

In M&S literature, the term hybrid modeling refers to studies combining M&S techniques with a wider array of approaches from disciplines such as applied computing, engineering, data science and operations research (Mustafee and Powell 2018; Tolk et al. 2021). For example, studies that combine methods in the implementation stage of a simulation study may consist of hybrid models using both simulation and analytical/mathematical techniques (Byrne and Bakir 1999), or those using simulation with machine learning (von Rueden et al. 2020). However, the lifecycle of a simulation study also includes several other stages, and there are opportunities for deploying cross-disciplinary methods that extend beyond implementation. For example, Soft OR approaches such as Soft Systems Methodology (SSM) have been widely used in the conceptual modeling phase of a simulation study (Pereira et al. 2015); Parallel and Distributed Simulation (PADS) techniques developed in computer science are routinely used for faster execution of large and complex models and for model interoperability (D'Angelo and Marzolla 2014; Taylor 2019). Similarly, IS/IT systems/artifacts such as data acquisition software (DAS), databases and real-time APIs owe their origin to applied computing and related fields (Figure 1). Such systems/artifacts developed outside our discipline enable the development of hybrid models using real-time data streams to drive RtS/DTs and represent a step-change from conventional modeling using historical data.

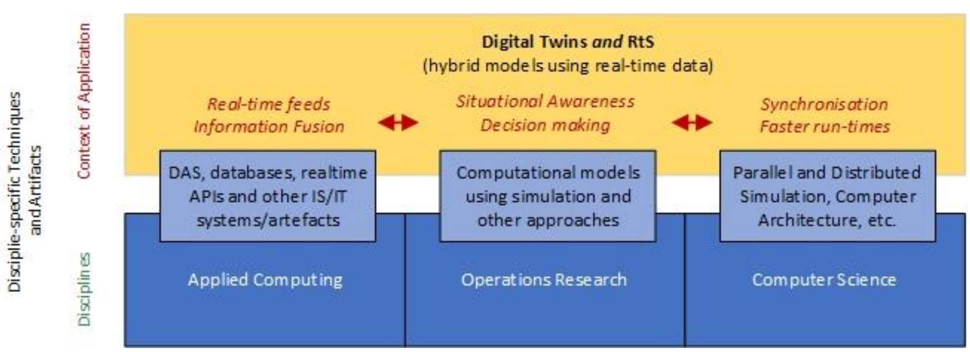


Figure 1: Real-time Simulation (RtS) and Digital Twins (DTs) use a mix of discipline-specific approaches to drive computational models with real-time data (adapted from Mustafee, Harper, and Viana (2023b)).

A critique of Digital Model (DM), Digital Shadow (DS) and DT: OR/MS models developed for healthcare operations management can be categorized as either offline models (conventional simulation models) or real-time models, namely, RtS and DTs; refer to Mustafee, Harper, and Viana (2023a) for the characterization of RtS and DT. In Manufacturing/Industry 4.0, the terms DM, DS and DT are frequently used to refer to a broader range of digital artifacts, including OR/MS simulation models and symbiotic simulations (Aydt et al. 2009) that connect to physical systems with functionality to, for example, control throughput rates in assembly lines. As healthcare is a service-based system, simulation results are generally communicated to stakeholders who are empowered to make decisions. Using Kritzinger et al. (2018) classification of DM, DS and DT, our conventional simulation is thus a DM with no automated data exchange between the physical object (the healthcare environment, in our case) and the simulation model. Business intelligence dashboards and Virtual Reality/Augmented Reality-based systems conform to the Kritzinger et al. (2018) definition of DS since a change in the physical system's state leads to a change in the digital model through one-way data flow. From the standpoint of M&S, we argue that the digital models classed as DS may not necessarily be computational models used for experimentation. Finally, our usage of both RtS and DT conforms to Kritzinger et al. (2018) definition of DT, which emphasizes two-way data flows but with one key difference. The data flow from RtS/DT to the physical environment is arguably akin to “decision flow". This again emphasizes the need for a decision-maker to assess competing simulated alternatives using RtS/DT real-time experimentation.

Our previous contribution to real-time modeling focused on characterizing RtS and DTs (Mustafee, Harper, and Viana 2023a) and challenges associated with data synchronization and experimentation (Mustafee, Harper, and Viana 2023b). This paper focuses on the core IS/IT systems that capture, store and relay data, which are prerequisites for developing real-world RtS/DTs.

3 LITERATURE REVIEW

Uhlenkamp et al. (2022) present a maturity model for the assessment of DTs in production and logistics under seven categories (context, data, computational aspect, model integration, control and human-machine interface). In developing the model, the study follows the approach presented by Becker et al. (2009) and augments it with a systematic literature review of 73 papers and the authors’ experience in DTs. Another example of a DT maturity model is the work by Papic and Cerovsek (2019), who present the *Digital Built Environment Maturity Model* to evaluate the level of digital capability of asset management organizations in three dimensions, namely, areas of digital capability (data management, data analysis and decision-making), supporting organizational environment (people, process and technology) and the five DT maturity stages (ad-hoc databases, DT formation, DT standard operation, DT real-time automation, and DT intelligence contextualization).

Klar et al. (2023) observed that several of the existing DT maturity level models were either domain-specific or viewed the system to be “twinned” in isolation; to address this, the authors consider interoperable DTs and present a maturity model that includes six levels, with levels 1 and 2 (replication and connection) categorized as a Digital Model, level 3 (synchronization) as Digital Shadow, levels 4 (interaction) and 5 (automation) as Digital Twin, and Level 6 (interoperability) as Connected Digital Twin. As will be discussed later in the paper, some elements of Klar et al. (2023) model, such as SA, simulations and real-time SA are concepts extensively used in our work. However, as discussed in Section 2, key differences exist in our use of the terms RtS/DT in relation to Kritzinger et al. (2018) classification of DM/DS/DT, the categories used by Klar et al. (2023).

Medina et al. (2021) present a four-level maturity model for DT implementation for original equipment manufacturers (OEMs) in the commercial aerospace industry (CAI). The authors used the Design Research framework (Hevner et al. 2004), which involves the collaborative building and evaluation of artifacts such as constructs, models or methods designed to meet business needs (Hevner et al. 2004), to consider the environment (CAI, OEMs, DT, business needs), the knowledge base (literature reviews, existing maturity models, industrial context, etc.) for artifact design (maturity model). The authors identified ten dimensions based on which maturity levels 1-4 were determined; this provided precision on the attainment level, per dimension, that an organization was expected to reach to claim a certain maturity level. The work by Medina et al. (2021) resonates with us since our previous work discussed participatory design research for developing RtS models in healthcare (Harper and Mustafee 2023). Although the study by Medina et al.

(2021) is on CAI OEMs, the dimensions related to 'Analytical Capability', 'Data Collection Frequency' and 'Model Update Frequency' are particularly important in the context of OR/MS simulation models and the authors' previous work (Harper, Mustafee, and Pitt 2023; Mustafee, Harper and Viana 2023a; Mustafee, Harper, and Viana 2023b; Harper, Mustafee, and Viana 2023). These dimensions are explored further.

Analytical Capability: Our previous work on increasing SA in healthcare through RtS identified opportunities for the deployment of descriptive, diagnostic, predictive and prescriptive analytics to enable increasing levels of SA (Harper, Mustafee, and Pitt 2023); this is similar to the monitoring, diagnostics, predictive and prescriptive functionality ('Analytical Capability' dimension) expected from CAI OEM DTs as they progress from maturity levels 1 to 4. Our SA framework acknowledges that 'monitoring' can be achieved through real-time data and descriptive analytics, 'predictive' capabilities can be built using time-series forecasting models, and 'prescriptive' element is introduced through the use of simulation models (which are our core computational models that drive our RtS/DTs).

Data Collection Frequency: For CAI OEM DTs the data collection frequency may be demand-based, it could be flight history data, in-flight data, or real-time data (Medina et al. 2021). Similarly, our previous work has discussed that the shift from conventional modeling (reliant on historical data), to RtS (using historical data with some real-time feeds) and finally to DTs (using real-time data) necessitates increasing data collection frequency (Mustafee, Harper, and Viana 2023a; Mustafee, Harper, and Viana 2023b).

Model Update Frequency: Medina et al. (2021) state that as organizations move from maturity levels 1 to 4, the model update frequency will reduce from weeks to days and then to hours and minutes. In the context of CAI OEMs, they identify a difference between data collection frequency and model update frequency. In our existing work, we note that RtS do not necessarily need to execute every time real-time data is received but are triggered when there is a breach in the normal KPI thresholds defined in the model (Harper, Mustafee, and Viana 2023). Our RtS/DTs are based on OR/MS computational models for operational decision-making (rather than engineering models that are the basis for CAI OEM DTs). In the context of our work, model update frequency will necessitate faster than real-time experimentation. However, the execution of the simulation experiments is not pre-determined (as with CAI OEM DTs); rather, they will be triggered if automated assessment of real-time inputs warrants further experimentation.

The definitions of DTs vary based on areas of application. Thus, it is not surprising that the fundamental building blocks for the DT maturity level models are also different. The literature would benefit from a maturity model specific to M&S, which, as its building block, acknowledges the need for IS/IT system integration - the enabler for real-time RtS/DT simulation experimentation. Real-time models have the potential to offer increasing levels of SA in healthcare operations management, which could be mapped to the attainment of well-defined maturity levels in IS/IT system integration. With this objective, the paper introduces the maturity model of IS/IT system integration for DTs in healthcare.

4 CASE STUDY ON IS/IT INTEGRATION OF PATIENT FLOW SYSTEMS

Healthcare IS/IT systems that capture the flow of patients in hospitals (scheduled care) and urgent and emergency settings are referred to as Patient Flow Management (PFM) systems. Conventional (offline) modeling mostly uses PFM data as historical snapshots. The case study motivating this research also has its genesis in our early work on offline modeling of Emergency Departments (EDs) and Minor Injury Units/Urgent Care Centres (MIU/UCCs), which are walk-in healthcare facilities for urgent care, in the South West of England. The work led to the *NHSquicker* project, which investigated the leveling of demand for urgent care by nudging users to visit certain facilities in priority order; the nudges were based on real-time data on waiting times and travel times and needed PFM system integration (Mustafee and Powell 2021). Our interest in IS/IT integration of PFM systems thus stemmed from the need to make summative data on patient numbers and waiting times available to users through an app. In terms of the overall system architecture, this meant that the PFM systems had to publish data in real-time; our backend *NHSquicker* system acted as a receptor of this data (server).

The UK has a publicly funded healthcare system called the National Health Service (NHS). NHS Trusts are free to procure IS/IT systems. Thus, both legacy and modern PFM systems co-exist in the urgent care ecosystem. Newer systems use an open architecture and technologies like web services and web APIs, which make it possible to query and publish data such as patient arrival, triage start and stop, and allocation of clinicians in real time (Warwick et al. 2021). Older systems, although they may capture numerous events of interest, are still fundamentally closed systems. For real-time M&S, the distinction between open and closed PFM systems assumes importance.

Through our longstanding *NHSquicker* project (since 2017), we experienced how some stakeholder organizations have transitioned their IS/IT systems, including implementing bespoke solutions, and made them more open. With several of the healthcare Trusts, the PFM system gradually offered increasing levels of functionality, for example, by first making data available internally as a business intelligence solution for decision support; next, by making a sub-set of data available to the public using information dashboards; finally, and through our involvement, integrating existing PFM systems with our backend *NHSquicker* system (this necessitated joint work with the IS/IT technicians at the NHS Trusts; on occasions, it also required PFM vendor support).

In developing the maturity model, we are not merely reflecting on capabilities that our stakeholder organizations have already acquired but also how they could gain further from deploying state-of-the-art solutions such as RtS and DTs; the latter may necessitate attaining higher levels of IS/IT integration. With the increase in maturity level, the PFM systems started publishing data. This allowed us to make ED/MIU/UCC waiting time available in real-time through the *NHSquicker* mobile app. We now use our real-time system to investigate the methodological advances needed to transition from offline modeling approaches to real-time M&S. As our experience of healthcare IS/IT systems is based on our work with PFM systems, the phrases “IS/IT system integration” and “PFM system integration” are used synonymously for the remainder of the paper.

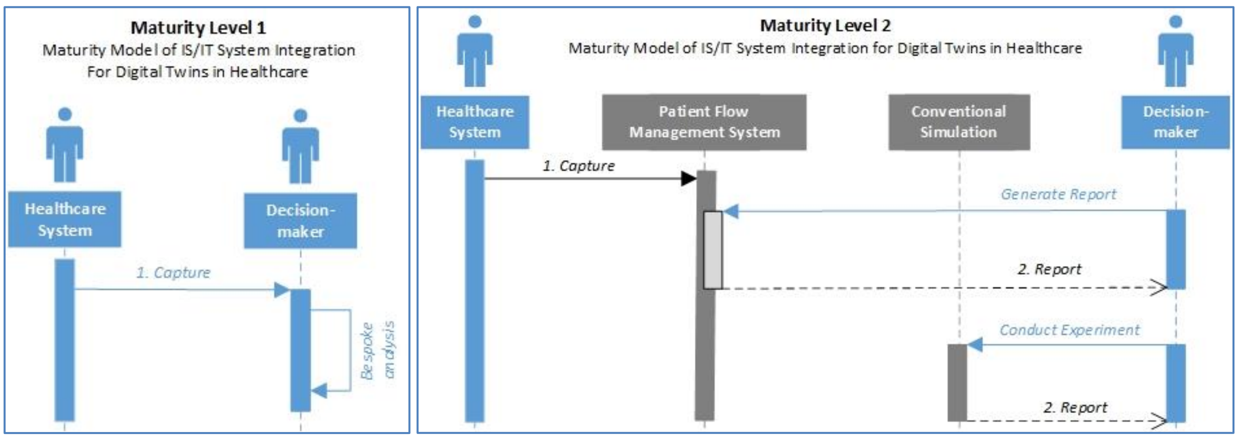
5 MATURITY OF PATIENT FLOW MANAGEMENT (PFM) SYSTEM INTEGRATION

5.1 Capture Data - Maturity Level 1 (ML-1)

Organizations in ML-1 lack IS/IT systems and automation. The defining characteristic of ML-1 is to capture data (the descriptor for the maturity level is *capture*), which allows bespoke analysis based on the decision-maker's needs. At ML-1, data is captured mostly using pen and paper, spreadsheets, or other general-purpose software. Thus, the receptionist may record information such as patient arrival, patient ID/address and symptoms. A medic may record health indicators like temperature and blood pressure, diagnosis and medicines that were prescribed. Data collected using pen and paper may be transferred to a computer program for analysis using Excel or other software. ML-1 is similar to Stage 1 (ad-hoc databases) of the *Digital Built Environment Maturity Model* (Papic and Cerovsek 2019). The UML interaction diagram in Figure 2 (a) illustrates the interaction between the environment actor (healthcare system) and the decision-maker actor (for simplicity, the decision-maker role is assigned to both clinical and non-clinical staff). UML is a visual modeling language frequently employed in IS/IT for the design of software artifacts. The interactions are primitive, with data from the environment captured manually and bespoke analysis undertaken occasionally. For simplicity, the diagram does not introduce an additional UML object to denote spreadsheets or other general software that may be used.

5.2 Report - Maturity Level 2 (ML-2)

Organizations that have invested in PFM systems are in ML-2. They build on the inherited ML-1 functionality of capturing data, albeit the process is now automated using specialist software, with the additional requirement that they can generate complex reports to support the business functions of the decision-maker. For example, the PFM may include a visual front-end for field selections for cross-tab reporting, etc., which generates reports using backend structured query language (SQL) queries. Thus, the descriptor for ML-2 is *report*. The PFM systems are also the repository of historical data that can be used for modeling purposes. The interaction diagram in Figure 2(b) introduces ‘PFM’ and ‘conventional simulation’ as two objects (indicated in grey) that are between the environment and decision-maker roles (in blue). The automation involved in capturing data from the environment is presented as a control element in the lifeline of the PFM object. In UML, control elements denote a period of time an object is performing an action. Control elements are illustrated as a vertical rectangle on the lifeline of an object (shown as a dotted line). Both the healthcare and the PFM actors include UML control elements that span their lifelines (shown in blue and grey, respectively); this indicates that any change in the environment (e.g., new patient arrival) will be automatically recorded in PFM as the virtual system runs in parallel to the physical system (i.e., when a facility is open, the PFM system is running). The second object introduced in Figure 2(b) is the 'conventional simulation'; as an offline model, the data requirement is mostly historical snapshots. With ML-2, the decision-maker invokes the PFM to generate reports and/or to execute an offline simulation model to determine credible alternatives. For simplicity, the dependence of the conventional model on PFM data is not explicitly shown.



(a) Maturity Level 1 (b) Maturity Level 2

Figure 2: (a) The defining characteristic of ML-1 is to "capture" data; there are no automated PFM systems; (b) Organizations in ML-2 will deploy PFM systems and generate "reports". The PFM will also serve as the primary source of data used for conventional (offline) simulations.

5.3 Publish Data – Maturity Level 3 (ML-3)

Organizations in ML-3 will *publish data* captured by PFM systems (the descriptor for the maturity level is *publish*). Other (external) systems could use this data for value addition through novel forms of transformation. In Section 4, we present a summary of our case study work on urgent care. Taking the same example, the organizations that relay data from PFMs such as *Symphony*, *EPIC* and *TrackCare* to our *NHSquicker* system (Mustafee and Powell 2021) are said to have reached a minimum ML-3. Figure 3 introduces an additional UML object 'information dashboard' (ID) to represent external systems that receive real-time feeds. Like ML-2, the UML control element for ID spans its lifeline, denoting that the external system runs in parallel to both the environment and the PFM system. From our experience, the data from the sender PFM system is generally set at pre-defined intervals, e.g., between 5-15 minutes. This is shown by introducing the loop element and the variable 'x', which signifies the minutes the system waits before sending the next batch of data. ML-3 builds on ML-1 and ML-2. Note that in ML-3, although the PFM systems publish data, it is not yet integrated with analytical artifacts that enable real-time M&S.

5.4 Integrate Callbacks - Maturity Level 4 (ML-4)

An organization with IS/IT integration level ML-4, will deploy PFM systems that await requests for real-time data from an RtS or other digital equivalents. Thus, in Figure 4, the UML object representing conventional simulation is replaced by RtS. Although conventional modeling will still be supported (per ML-3), this will not harness the true potential of the higher level of IS/IT integration that has been achieved.

The descriptor for the maturity level is *integrate* since it is not merely a publisher of data (ML-3) but rather integrates functionality that allows a PFM system to listen for incoming requests (indicated with the new UML loop element and an arrow on the PFM control element), process the request (shown as an overlay of the orange control element on the main PFM element) and then send data to the requestor system (RtS). In technical terms, ML-4 implementation will require PFM systems to support technologies such as web and real-time APIs, with some degree of bespoke development based on the needs of the RtS.

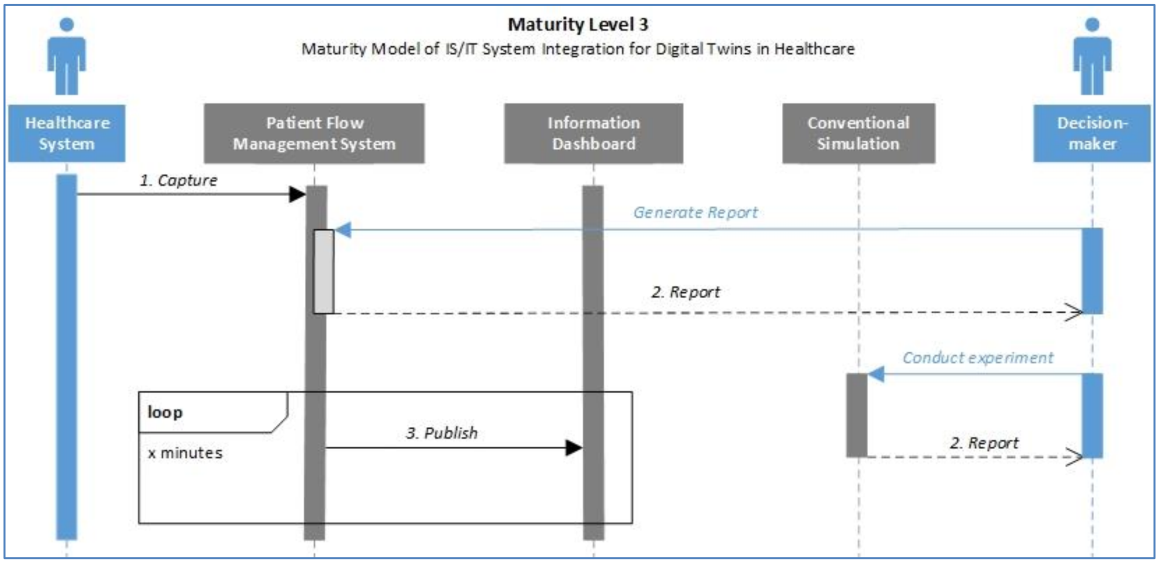


Figure 3: ML-3 builds on ML-1 and ML-2, and its defining characteristic is the ability to "publish" data.

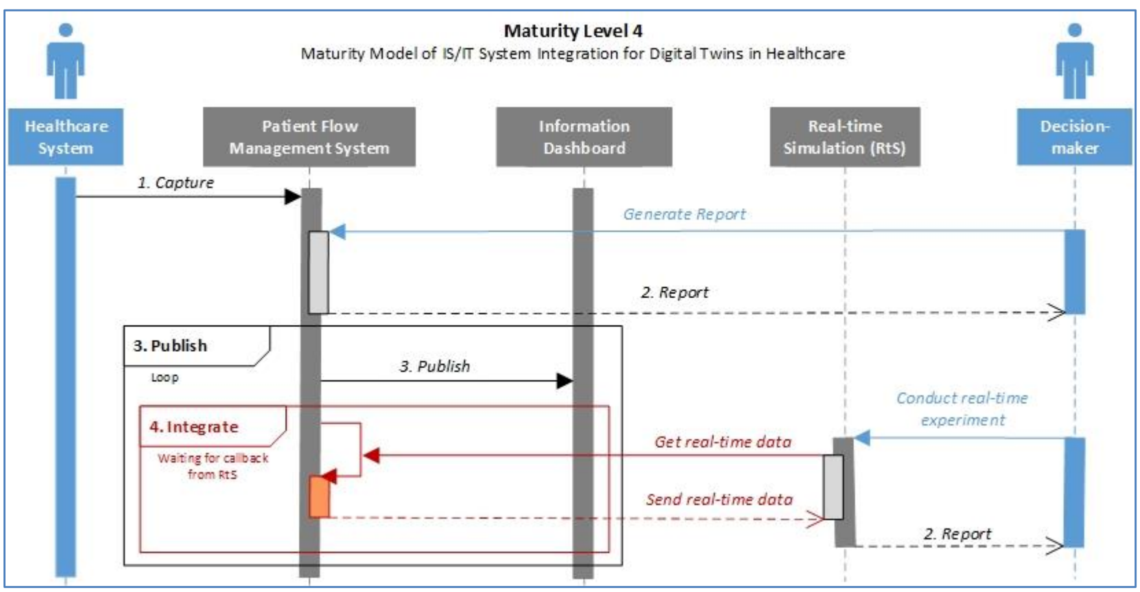


Figure 4: The defining characteristic of ML-5 is for the PFM system to implement a "callback" function.

5.5 Execute Model – Maturity Level 5 (ML-5)

ML-5 is the highest level of our maturity model. Building on the move from manual to automated systems (ML-1 to ML-2), and with increasing levels of IS/IT integration achieved in ML-3 and ML-4, PFM systems at ML-5 will be able to trigger DT experimentation. The experiments may be triggered in response to the real-time key performance indicators (KPIs) values (calculated by the PFM systems continuously) breaching the normal operational KPI thresholds defined in the system. Thus, the descriptor for ML-5 maturity level is *trigger*.

In Figure 5, the UML object representing RtS (see Figure 4) is replaced by DT. Per ML-4, RtS is still a possibility (indeed, Figure 5 includes the "integrate" element where the DT assumes a role similar to RtS and requests real-time data from the PFM system), but the ML-5 system is not being used to its full potential. The role of the decision-maker is also important in relation to ML-4 and ML-5. In ML-4, the decision-maker is the initiator of the RtS; they may rely on information dashboards (ML-3) to assess the need for experimentation. In ML-5, automation replaces the role of decision-maker as initiators of real-time experiments; all requests for data, real-time assessment of KPIs, triggers for experimentation and results capture are performed through automated system-level coordination between PFM systems and the DTs. In this heightened state of automation, the role of the decision-maker is still significant; they assess the results of the DT simulation and implement changes towards returning the physical (healthcare) system to normal operation thresholds. Finally, Figure 5 shows that an ML-5 system may receive the results of a DT simulation in the form of simulated KPIs. This allows the triggering mechanism in PFM systems to become increasingly intelligent, mimicking the behavior of a decision-maker who may rely on experience to ascertain the need for experimentation.

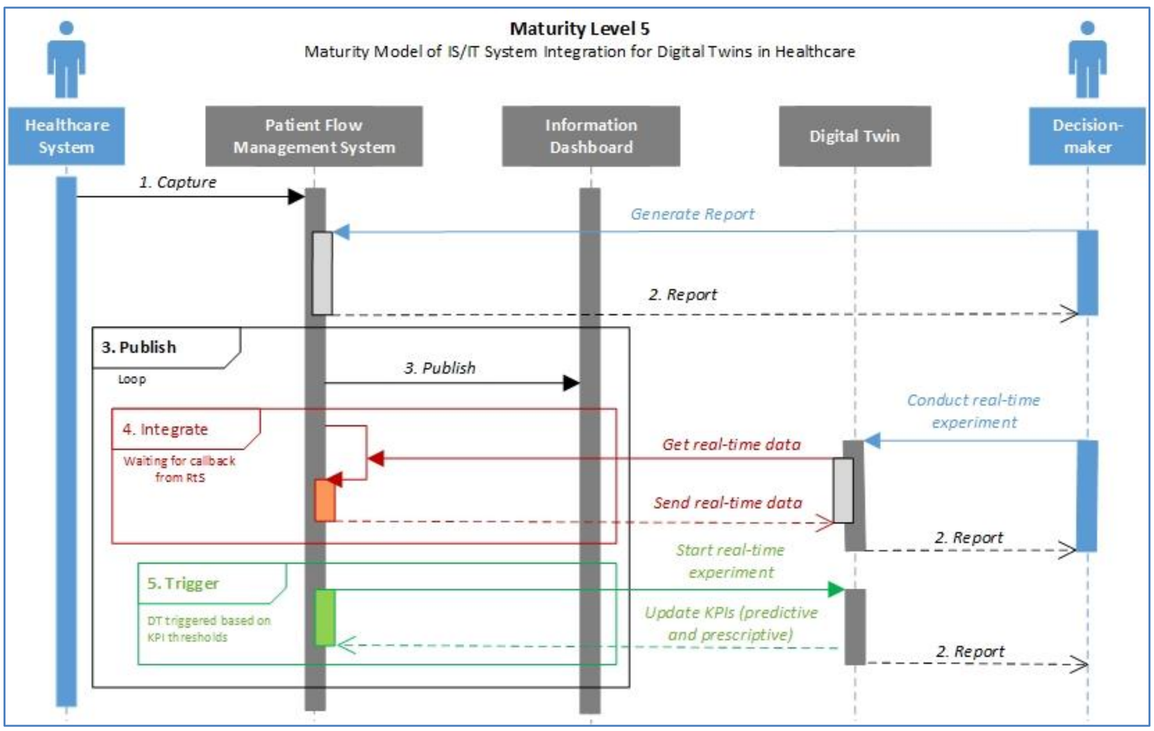


Figure 5: The highest level of maturity (ML-5) will enable PFM systems to "trigger" real-time experiments.

6 MATURITY MODEL FOR IS/IT SYSTEM INTEGRATION FOR DIGITAL TWINS

The previous section has identified five levels of IS/IT maturity (ML-1 to ML-5). The move from initial stages to more advanced stages is achieved when healthcare organizations have attained higher levels of integration capabilities; this also offers them the opportunity to lower their dependence on historical data analysis in favor of real-time modeling, the latter contributing to enhanced situational awareness (SA) and making organizations better prepared in meeting operational performance metrics. Our maturity model refers explicitly to DTs; this signals that organizations should aim to deploy decision-making tools and approaches that are the current state-of-the-art (like DTs), an aim achieved by attaining ML-5. Thus, by signaling what is possible through advanced OR/MS artifacts and what this necessitates in terms of interfacing systems with models, the aim is to use our maturity model to motivate organizations to attain higher levels of system integration.

Figure 6 presents our maturity model, which comprises three axes (x-axis, y-axis, and y'-axis), which are discussed next:

- The x-axis, a Likert Scale of 1-5, represents the increasing IS/IT system integration capability achieved by an organization as they move through the maturity stages of "capture", "report", "publish", "integrate" and "execute".
- The y-axis conveys the data requirements for OR/MS artifacts. For ML-1 and ML-2, the OR/MS artifacts rely only on historical data. For ML-3 to ML-5, the bidirectional arrows communicate the increasing reliance of these artifacts on real-time data.
- An additional element on the y-axis is the "M&S perspective" (the y'-axis) represents artifacts that are realized at different maturity levels (x-axis) based on the mix of historical and real-time data (y-axis); in other words, artifacts denoted through the y'-axis are at the intersection points of x and y axes, which gives the appearance of a stacked histogram.

In our maturity model, increasing IS/IT integration levels presents opportunities for newer and more advanced analytical solutions. These new modeling artifacts are illustrated in cyan. ML-1 is not considered since it is a manual system, and only bespoke analysis is possible (Section 5.1). At ML-2, PFM systems are first introduced. They enable automation regarding report generation and the use of PFM databases; the latter are repositories for historical data which can be used for conventional offline modeling. Thus, at ML-2, we identify two new analytical artifacts - 'conventional simulation models' and 'automated analysis/reporting' (Section 5.2); both are identified in cyan. IS/IT systems at ML-3 publish data and make them available to receptor systems. This enables the development of artifacts external to the PFM systems, like a 'real-time information dashboard' (Section 5.3). As new levels of maturity build on the attainments of prior levels, we see that ML-3 benefits from both automated reporting and the opportunity to develop convention simulations (both requiring only historical data); however, the highest level of OR/MS artifact attainment for ML-3 are the online information dashboards (Section 5.3). In ML-4, having achieved the maturity level with the descriptor "integrate", the organizations are, for the first time, technologically ready to interface the PFMs and OR/MS models for developing RtS models that allow real-time experimentation (Section 5.5). Finally, when healthcare organizations reach ML-5, they are ready to deploy DTs triggered by PFMs (Section 5.5). In Figure 6, the online information dashboards, RtS and DT are all shown in cyan as they represent the highest attainment of OR/MS artifacts in ML-3, ML-4, and ML-5, respectively.

As organizations advance through maturity stages, the potential contribution of IS/IT system integration capability to organizational SA increases. Real-time information contributes to awareness of the current system state by updating decision-makers' knowledge to support fast decisions (Harper, Mustafee, and Pitt 2023). This is achieved by enhancing SA, a knowledge state that is an important constituent in subsequent cognitive decision processes (Endsley 1995). With sufficient SA, a match between experience and knowledge about the current system state can enable decision-makers to determine an appropriate course of action. Endsley's (1995) model of SA defines a closed-loop system between a decision-maker, and a physical system. SA is defined as "the perception of the elements in the environment, within a volume of time and space, the comprehension of their meaning, and projection of their status in the near future" (Endsley and Jones 2024), referring to ascending levels of SA. In Figure 6, five levels of SA are identified and which correspond to the increasing maturity levels of IS/IT system integration (SA1 to SA5). A feedback loop from the physical system represents the outcomes of action; the feedback may not be immediate, as the outcomes of actions need to be perceived and comprehended. Real-time information supports this feedback loop by updating decision-makers' immediate knowledge. Higher quality real-time information has a higher contribution to SA. At ML-4 and ML-5, RtS and DT can be seen as fulfilling certain roles alongside human decision-makers, as their functions have progressed from observer, to analyst, to decision-maker, to actuation and communication, increasingly informing the ascending levels of SA (Agrawal et al. 2023).

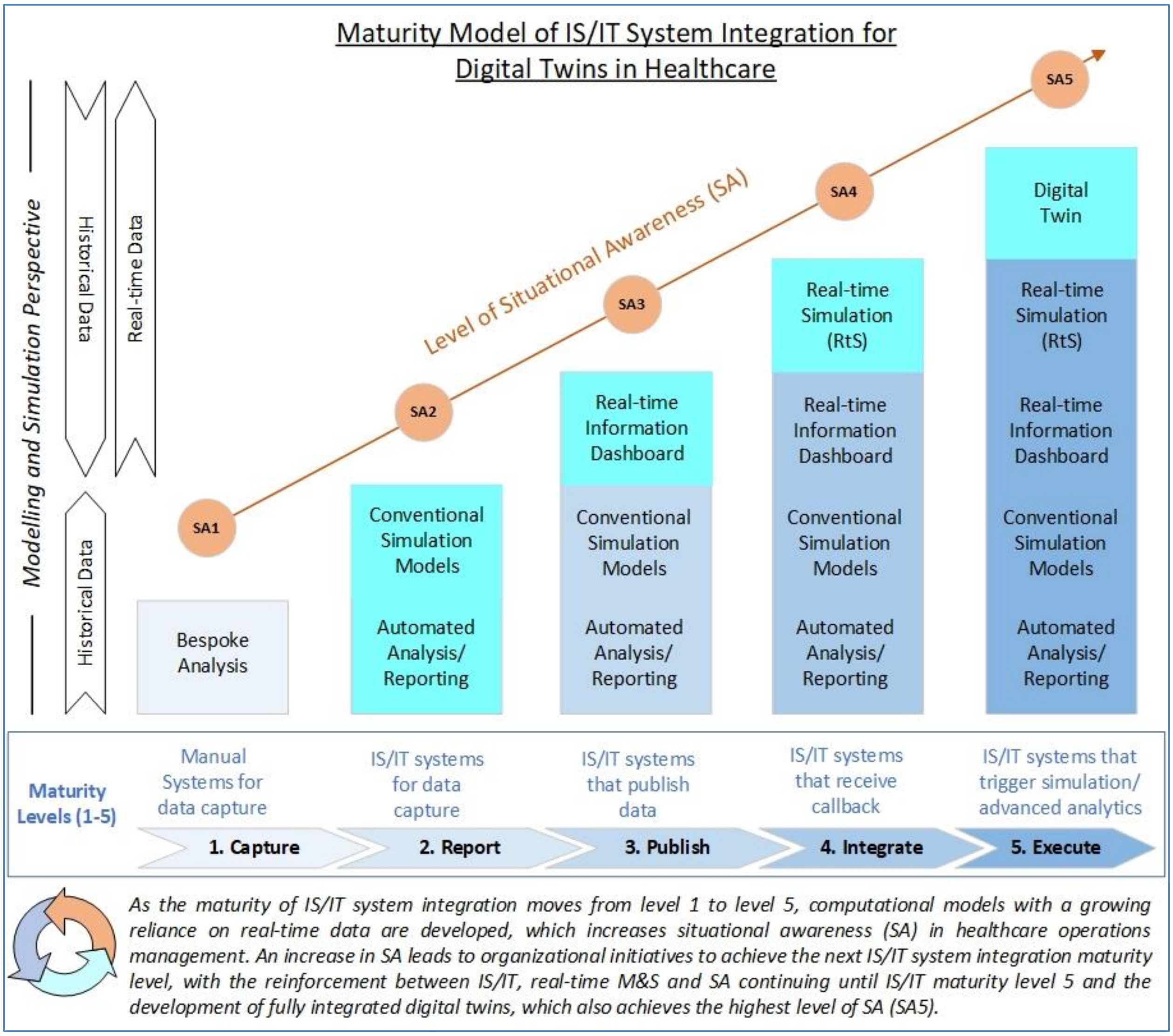


Figure 6: Maturity model of IS/IT system integration for DTs in healthcare consists of five maturity levels (capture, report, publish, integrate, and execute).

7 DISCUSSION AND CONCLUSION

Maturity models consist of a sequence of discrete MLs representing an evolutionary path of improvement from an existing state to a future anticipated state; advancing between the two extremes involves a continuous progression of organizational capabilities or process performance (Becker et al. 2009). In our maturity model, the IS/IT systems are PFMs. The first stage is ML-1, representing a lack of automation. The conception of total maturity is achieved at ML-5 with PFMs intelligently triggering real-time experiments mimicking the behavior of a decision-maker who may rely on experience to ascertain the need for experimentation. ML-5 can theoretically be generic enough to consider a future AI-based system (e.g., multi-agent-based RL systems) for such triggering mechanisms, replacing a human. However, this is likely to be only applicable to a very small subset of decision-type problems that are highly unlikely to directly affect patient safety. From an M&S perspective, a move towards higher maturity levels is accompanied by opportunities to deploy analytical artifacts with increasing reliance on real-time data, achieving higher degrees of SA in healthcare organizations. The model explicitly refers to DTs to signal that organizations should aspire to deploy the latest advances in decision-making tools, which will, in turn, necessitate attaining the highest level of IS/IT system integration.

The model was developed based on our experience with a long-running project on urgent and emergency care, which necessitates integrating existing healthcare IS/IT systems with our *NHSquicker* solution (Mustafee and Powell 2021). Through this work, we found that our stakeholders – the NHS Trusts in the South West of England – have achieved ML-2, and the majority are in ML-3 (our intervention also contributed to the translation from ML-2 to ML-3). For our empirical work on Real-time Simulation (RtS) (Harper, Mustafee, and Viana 2023), we are using the *NHSquicker* system to implement the ML-4 functionality of "callback". As our platform receives real-time data from several ML-3 PFM systems (ML-3 descriptor "publish data"), it serves as a proxy to the desired future state where the stakeholder will invest in achieving higher IS/IT PFM integration levels. Such investment will happen when they see the value of real-time modeling using RtS and DTs; our ongoing work on RtS using our backend system is a step in that direction.

Our maturity model focuses on healthcare IS/IT systems. However, data conducive to real-time modeling exist in other clinical and administrative IS/IT systems. Similarly, specialized services like the ambulance service may deploy systems for ambulance dispatch that record the availability and location of assets. Manufacturing, maintenance, repair and operations (MRO), supply chain and logistics and other domains have specialist IS/IT systems that similarly capture routine data to support business operations. Thus, our maturity model applies to the general class of IS/IT systems that capture operational data (e.g., DAS); data that can be used to develop various forms of modeling artifacts, including offline simulations, RtS and DTs.

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AUTHOR BIOGRAPHIES

NAVONIL MUSTAFEE is Professor of Analytics and Operations Management at the University of Exeter Business School, UK. His research focuses on hybrid modeling and real-time simulation, and their application in healthcare, supply chain management, circular economy and climate change adaptation and resilience. He is a Joint Editor-in-Chief of the Journal of Simulation (UK OR Society journal) and leads the JOS Africa Focus initiative. His email address is n.mustafee@exeter.ac.uk.

ALISON HARPER is a Lecturer in Operations and Analytics at the Centre for Simulation, Analytics and Modelling, University of Exeter. Her research interests include applied health and social care modeling and simulation, real-time simulation, and reusable modeling in healthcare. Her email address is a.l.harper@exeter.ac.uk.

JOE VIANA is a Postdoctoral Fellow at the Department of Industrial Economics and Technology Management, Norwegian University of Science and Technology. He is also affiliated with the Center for Service Innovation, St. Olav's Hospital, Norway, and the Dept. of Accounting & OM, BI Norwegian Business School. He gained his PhD from the University of Southampton. His interests are in the applications of simulation to improve the operation of health systems. His email address is joe.viana@ntnu.no.

THOMAS MONKS is an Associate Professor of Health Data Science at the University of Exeter Medical School. His research interests include open science for computer simulation, urgent and emergency care, and real-time discrete-event simulation. His email address is t.m.w.monks@exeter.ac.uk, and his website is https://arc-swp.nihr.ac.uk/about-penarc/people/tom-monks/.