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A Framework for Data-Driven Process Optimization: The Process Data Quality Maturity Model

By Evangelos Xevelonakis, Simon Moser± & Janis Hummel○*

The successful implementation of data-driven process technologies requires not only a mature digital infrastructure but also high-quality process data. This paper introduces the Process Data Quality Maturity Model (PDQ MM), a comprehensive framework designed to assess and enhance process data quality. The PDQ MM focuses on the quantification of seven core dimensions - Completeness, Correctness, Credibility, Consistency, Availability, Timeliness, and Interoperability - alongside the four supporting dimensions Governance, Strategy, Technology, and Culture. By integrating quantitative and qualitative measures, the model addresses limitations in existing maturity frameworks, which often overlook process-specific data quality. A financial process case study illustrates the model's application, demonstrating strengths and weaknesses of not only the selected case but also the PDQ MM. Conducting a comparative analysis with another Digital Maturity Model highlights the PDQ MM's unique value in providing actionable, data-driven insights. Despite its strengths, the model's process-specific focus, resource intensity, and reliance on subjective inputs pose challenges, which future research should address through automation and scalability improvements. Overall, the PDQ MM offers organizations a robust tool for assessing digital maturity, optimizing processes, and unlocking the full potential of analytical techniques such as process mining, paving the way for more effective decision-making and sustained organizational growth.

Introduction

In today's rapidly evolving digital landscape, organizations are increasingly leveraging data-driven methodologies to enhance operational efficiency and maintain a competitive edge. Various optimization methods, ranging from Lean approaches to Process Mining and even AI-driven automation, depend on the extraction of actionable insights from event logs to optimize business processes (van der Aalst, 2016). However, the efficacy of these approaches is intrinsically linked to the digital maturity of an organization as well as the quality of the underlying data. High-quality data ensures accurate process models, while poor data quality can lead to misleading analyses and suboptimal decision-making (Bose et al., 2013).

Traditional maturity models, such as the Capability Maturity Model (CMM), have been instrumental in assessing organizational processes and guiding improvements (Paulk et al., 1993). However, even more modern approaches of

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these models often lack a specific focus on process data quality within the context of process optimization. To address this gap, the Process Data Quality Maturity Model (PDQ MM) is introduced, offering a structured framework to evaluate and enhance process data quality.

The PDQ MM is grounded in established data quality frameworks and tailored to the nuances of digital process optimization. It encompasses seven core dimensions - Completeness, Correctness, Credibility, Consistency, Availability, Timeliness, and Interoperability (Goel et al., 2022). Additionally, the model incorporates supporting dimensions such as Governance, Strategy, Technology, and Culture, recognizing that data quality is influenced by broader organizational factors (Brock et al., 2024).

This paper delineates the theoretical underpinnings of the PDQ MM, details the methodology for assessing each dimension, and presents a case study application within a financial process to demonstrate its practical utility. By providing a comprehensive tool for evaluating data quality maturity, the PDQ MM aims to facilitate more effective process optimization methods and, consequently, more informed organizational decision-making.

In section 2, current literature on maturity models will be reviewed, followed by an explanation of the methodology used in section 3. Section 4 will outline the dimensions of the PDQ MM, while an empirical application and discussion of the model is provided in section 5, including its limitations. Lastly, concluding remarks are presented in section 6.

Literature Review

Before the development of a maturity model on process data quality, it is essential to review existing maturity frameworks to understand their contributions and limitations. Various maturity models have addressed organizational development, digital transformation, and process optimization, yet few have provided adequate insights into process-specific data quality, a critical component for effective digital maturity and data-driven process optimization. This review evaluates prominent maturity models and outlines their limitations in relation to the proposed model's focus on data quality.

Traditional Maturity Models

Foundational models, such as the CMM (Paulk et al., 1993) and Capability Maturity Model Integration (CMMI, Chrissis et al., 2011), have established key principles in organizational capability development, providing structured frameworks for evaluating process maturity. These models have been influential in guiding general organizational improvements, offering systematic stages for assessing maturity. However, their thematic breadth often limits their relevance for assessing digital maturity, particularly at the level of process-specific data quality. As these models were not designed with data quality in mind, they provide limited criteria for evaluating data reliability, accuracy, or completeness within process contexts.

This short review implies that, despite their historical importance and relevance, foundational maturity models fall short in addressing detailed data quality metrics, necessitating models that can more precisely evaluate process and data maturity.

Digital Maturity Models

Digital Maturity Models (DMM), including those developed by Bitkom (2022) and Berghaus and Back (2016), have expanded maturity assessment to encompass digital transformation across entire organizations. These models provide a holistic view of organizational digital maturity, typically through qualitative assessments via surveys and interview-based evaluations. Despite their comprehensive scope, these models often lack depth in process-specific or data-centric metrics, focusing on high-level assessments rather than measurable process quality criteria. This lack of quantitative detail can lead to superficial assessments, making it challenging to gain actionable insights into digital maturity on a granular, process-by-process basis.

DMM models therefore enable a simple assessment of digital maturity but their reliance on qualitative metrics restricts their applicability for detailed process and data assessments, underscoring the need for quantifiable criteria to evaluate process data quality rigorously.

Business Process Maturity Models

Business Process Maturity Models (BP MM) represent a framework for evaluating the quality of business processes, generally emphasizing process efficiency and optimization. Fisher (2004) differentiates between two interpretations of process quality: process efficiency (the operational effectiveness of processes) and data quality (accuracy and completeness of data within processes). However, BP MM primarily focus on the efficiency aspect, potentially overlooking foundational aspects of data quality essential for process accuracy and consistency. Consequently, these models may inadequately support the data quality prerequisites needed for robust digital maturity assessments.

Despite the importance of process efficiency, its' measurements rely on the underlying data's accuracy. In the investigated context, BP MM would hence benefit from incorporating data quality as a foundational metric, addressing this gap in maturity model development.

Business Process Management Maturity Models

Process Management Maturity Models (BPM MM) contribute valuable insights into data management practices within organizations, focusing on data handling and governance (Ryu et al., 2006). However, these models generally address data management functions without explicitly evaluating data quality dimensions, such as data accuracy, integrity, or relevance. This narrower focus limits their relevance for comprehensive maturity models aimed at assessing data quality in process-specific (optimization) contexts.

BPM MM models, while valuable for data governance, do not provide sufficient frameworks for assessing data quality directly due to their focus on data management. This limitation further highlights the need for a maturity model that integrates data quality evaluation into the broader maturity assessment framework.

Event and Log Data Quality Models

Event and Log Data Quality Models, such as those outlined in the IEEE PM Manifest (Van der Aalst et al., 2012) offer a granular approach to data quality by focusing on the fundamental building blocks of processes: event and log data. These models emphasize the importance of accurate and reliable data for understanding process flows and evaluating process quality. However, the literature on event data quality often lacks consensus on clearly defined and measurable quality dimensions, with little standardization across studies.

While event and log quality models are invaluable for establishing data quality dimensions and tackle the problem put forward in this work, a lack of standardized metrics hinders their application in systematic maturity assessments. These models highlight the importance of reliable data in digital process optimization but require clearer, more universally accepted quality metrics.

Process Mining Maturity Models

Process Mining Maturity Models (PM MM) are an emerging field that underscores the importance of readiness for PM as a form of data-driven process optimization within digital maturity frameworks. Brock et al. (2024) recently indicated a growing need for specialized maturity models in PM, yet existing frameworks often lack depth and specific criteria to comprehensively assess data quality. Despite the relevance of PM to digital maturity, these models are limited in their assessment of data quality, which is critical for an effective evaluation and implication of process optimization methods.

The alignment of PM MM intentions with data quality assessment objectives suggests potential compatibility with a process data quality maturity model. However, these models require further development to enhance their data quality focus, supporting a more robust framework for digital maturity.

In summary, existing maturity models — from traditional frameworks like CMM to emerging PM Maturity Models — offer important foundational elements for assessing digital maturity but often lack a dedicated focus on process-specific data quality. These limitations reveal the need for a process data quality maturity model that emphasizes quantifiable, data-centered criteria. Such a model would support a more accurate assessment of digital maturity and support process optimization, bridging current gaps with a strong emphasis on data quality for actionable insights.

Methodology

After having discussed the literature on the topic and having recognized the importance of objective measures of process data quality, the identification of potential model dimensions becomes the primary methodological concern. For this, the discussed literature on digital maturity models was complemented with further literature on (process) data quality.

Suriadi et al. (2017) discuss several approaches to measuring data quality and firstly state, that "*an event log needs to contain at minimum, enough information such that every activity can be described to a case and can be ordered via, for example the timestamp*" (p. 133). This emphasizes the basic importance of event data characteristics prior to a potential model application. Bose et al. (2013) mention another fundamental requirement for event log data quality by pointing out the impact of missing data (no data), incorrect data (wrong logging), imprecise data (coarse logging) and irrelevant data (no *as-is* use of data).

In broader approaches like the one from Wand and Wang (1996), data quality is defined by the dimensions Completeness, Unambiguity, Meaningfulness and Correctness. These cover the importance of all real-world states being able to be represented in an information system (Completeness), two real-world states not being able to have the same state in an information system (Unambiguity), states in an information system being able to be mapped back to a real-world state (Meaningfulness) and all real-world states being mapped to the correct information system state during operation (Correctness).

Batini and Scannapieco (2006) conceptualize data quality as a combination of Accuracy, Consistency, Currency, Timeliness & Volatility and Synchronization between different time series. Accuracy is further divided into Syntactic Accuracy, which covers the closeness between recorded value and corresponding definitions, and Semantic Accuracy, which includes the closeness between recorded value and true value. Hereby, the framework covers closeness between recorded value and real-life phenomenon, the potential violation of semantic rules, changes and updates to data in time and the integration of data having different timestamps.

Mentioned data quality dimensions in other research typically include Accessibility, Accuracy, Completeness, and Consistency (Lee et al., 2006; Ofner et al., 2013; Pipino et al., 2002; 2005; Wang et al., 1995). These are also mentioned in the Iso norm on data quality (ISO15012), which differentiates between inherent data quality measures (Accuracy, Completeness, Consistency, Credibility & Currentness), system-dependent data quality measures (Availability, Portability & Recoverability) as well as combinations of both (Accessibility, Compliance, Confidentiality, Efficiency, Precision, Traceability & Understandability).

After getting a hold on the most frequently mentioned dimensions of (event) data quality and identifying similarities, differences and overlaps between different concepts, literature on digital maturity models and on process data quality was combined into a framework which enabled the definition of seven central, quantifiable and objective dimensions measuring process data quality as well as several supporting dimensions. By integrating these dimensions into a maturity model, the PDQ MM emerged, which will now be discussed in the following. After having discussed the identification of the dimensions in this part, focus will now be on the quantification and measurement of them.

Results

The essential intent and characteristics of the PDQ model can be summarized as follows:

- The PDQ model considers process data quality to be the most important predictor/variable for Digital Maturity, especially when focusing on the successful implementation of process optimization methods.
- Through a profound literature review, seven central dimensions of the PDQ MM could be defined: Correctness, Credibility, Consistency, Completeness, Availability, Timeliness, and Interoperability.
- Unlike other models, The PDQ MM aims for a quantitative measurement of variables (as far as possible). This should enable more valid, objective and comparable results. Each variable is assessed on a scale from 0 to 10. Until the final score, values are always rounded to two decimal places.
- In addition to a focus on quantitative assessment which makes results much more comparable and meaningful, this model still wants to consider organizational and branch differences and therefore often includes parameters, which must be defined by the model applicant. In this way, the model isn't generalized too much and doesn't lose its case-specific applicability and interpretation.

Having defined the seven main dimensions, the question of data differentiation arises. Especially regarding dimensions like Completeness or Correctness, it doesn't seem fair to apply the scores to all kind of event data in the same way. This supports some kind of differentiation in importance of event data due to differences in the amount of information they provide. While considering CaseID, Timestamps and Activity as the most central entries of event data (de Weerdt & Wynn, 2022), the following distinction is suggested:

Level 0: no event data is collected
Level 1: event data is collected, but not all of three central variables
Level 2: most central event data entries are collected (CaseID, Timestamps, Activity)
Level 3: a broad range of additional event data is collected (user/actor information, status, severity level, source/destination address, correlation ID, etc.)

This definition of levels brings layers into the maturity model. First, the organization is assessed by the amount and variety of collected event data (Level) and afterwards, the seven dimensions are assessed on a scale from 0-10 for this respective level (score). This differentiation means that an organization can have a rather low amount of collected event data (e.g. only timestamps and status, Level 1), but can score high in the model nonetheless. This may even provide more information than scoring low on a higher level. Therefore, when achieving high maturity on a rather low level, the organization should start thinking about collecting more event data and achieve high scores on a higher level. It is important to bear in mind that an organization should at least reach the requirements of Level 2 to successfully improve the data quality of their processes.

Central Dimensions

To account for the varying relevance of the seven central dimensions, an intra-level weighting scheme was developed (see Table 1). The allocation of weights is based on a comprehensive review of recent literature on data quality. Prior research consistently highlights Completeness and Correctness (often referred to as Accuracy) as the most critical determinants of overall data quality and "fitness for use" (Ramasamy & Chowdhury, 2020; Suriadi et al., 2017; Pipino et al., 2002). Missing case identifiers or timestamps, for instance, can render entire event logs unusable, while inaccurate values directly lead to misleading analyses and erroneous managerial decisions. Accordingly, both dimensions are assigned the highest weights (0.20 each). The dimensions Credibility, Consistency, and Interoperability are weighted moderately (0.15 each), reflecting their established role in fostering trust, syntactic stability, and cross-system integration (Pipino et al., 2005; Verhulst, 2016; Ford et al., 2007). By contrast, Availability and Timeliness receive the lowest weights (0.075 each). While both are frequently discussed in data quality research (Batini et al., 2009; Gong et al., 2023), their relative importance is considered lower in the context of process optimization, where retrospective analysis typically dominates over real-time applications. This weighting scheme ensures a balanced representation of all central dimensions while emphasizing those most critical to the successful use of process data for optimization purposes.

Table 1. *Intra-Level Weights of the Central Dimensions*

Dimension	Weight
Completeness	0.2
Correctness	0.2
Credibility	0.15
Consistency	0.15
Availability	0.075
Timeliness	0.075
Interoperability	0.15

The model's key dimensions and their measurement are now presented in more detail, focusing on objectivity and quantifiability.

<u>Completeness</u>

By simply measuring to which extent event data is missing, Completeness is central.

According to Verhulst (2016), three different checks assess this dimension. Through this variety of measurement methods, the model is suitable for assessing different data formats (e.g. data with or without transactional information) and data of different importance (e.g. Case ID is more important than some arbitrary other measured variable). After some minor adjustments, they can be used in a combined measure of completeness as they are all on a scale from 0-10:

- *Missing values (MV)*: For each percentage of missing values (e.g. entries that equal "empty", "ntb", "null", "NB" or if the length of an entry equals 0), one point is deducted from the highest score of 10. The minimum score is 0.
- *Transactional information (TI)*: Using the organization extension of the XES standard, which contains information about whether only the complete times, or also start time etc. have been logged, four options emerge: (Note: There is no value of 0 as the TI-score enters multiplicatively to the resource check when scoring transactional information)
    - No transactional information present: 1.
    - Only the complete or start times are logged: 6.
    - Complete and Start times have been logged: 9.
    - More than those two timestamps have been logged: 10.
- *Resource check (RC)*: For each event, check if the resource that generated the event has been logged as an attribute as well. This way the resource for that specific event is present, which is important for responsibility concerns. Let p be the % of the events that have not got a source logged (and hence $1 - p$ the % of the events that have got a source logged). Note that i can take any value between and including 0-100 ($i \in [0,100]$).
    - If $p \in [5,100] \rightarrow RC - Score = 0$
    - If $p \in [3,5) \rightarrow RC - Score = 2.5$
    - If $p \in [1,3) \rightarrow RC - Score = 5$
    - If $p \in (0,1) \rightarrow RC - Score = 7.5$
    - All events have an assigned resource $\rightarrow RC - Score = 10$

For most columns, a MV score can be calculated, which is normally sufficient. Due to the increased importance of Case ID, Timestamp, and Activity, they require a harsher assessment like the Resource check calculation. For Case ID, Timestamps and Activity, the MV score is therefore replaced by the RC approach, measuring the missing number of Case IDs and missing activity logs respectively more strictly. For timestamps, the RC measure is further complemented by the TI score, by multiplying the RC score by TI/10.

<u>Correctness</u>

Pipino et al. (2005) define Data Correctness as follows: "*Given that a data unit is complete, then the data unit is incorrect if either of the two following conditions hold: (1) the data unit maps back to a meaningless real-world state, or (2) the data unit maps back to a wrong real-world state. Otherwise, the data unit is said to be correct*" (p. 80). Even if data is consistent and complete, it isn't necessarily correct. The assessment of Data Correctness therefore relies on knowing, what data counts as "meaningless" or "wrong". If this can be assessed, the event data correctness is a simple fraction of correct data from all data (Wand & Wang, 1996). This dimension covers semantic correctness, while syntactic correctness is covered by the Consistency dimension (Wang et al., 1995; Azeroual et al., 2018).

As in Completeness, the more important data types can be assessed by the RC calculation, while the others' score is defined by the MV approach.

In practice, determining what constitutes a correct data unit and what is an error requires a set of clearly defined criteria. For example, the degree of precision or accuracy respectively must be specified. For every column, a tolerance range has to be specified which we suggest being organization-specific and therefore defined by the model applicant. Nonetheless, it is suggested to leave less leeway when evaluating the three central event data types.

Credibility

In some cases, comparing event data to its real-world state is not that easy and its assessed correctness may be deceitful. Especially when event data is plausible, its credibility/believability plays a central role for assessing its quality. Data Credibility therefore cannot be assessed simply by looking at event data. It focuses on how event data is considered by users regarding its reliability and therefore needs to be applied in an interview setting.

Pipino et al. (2002) suggest the division into:

- *credibility of a data source*
    - How would you rate the trustworthiness of the data's origin?
    - How would you rate the reliability/reputation of the entity or system providing the data?
    - How would you rate the transparency of the event data collection process?
- *comparison to a commonly accepted standard*
    - How would you rate the data in comparison to established industry or domain-specific standards?
    - How would you rate the data in comparison to established industry or domain-specific guidelines?
    - How would you rate the data in comparison to established industry or domain-specific benchmarks?
- *previous experience*
    - How would you rate the past interactions with the data?
    - How would you rate the knowledge gained from working with the data over time?
    - How would you rate the consistency of data generation regarding its content?

Each category can be assessed on a scale from 0-10 by the model applicant. Then, the final score is averaged by equally weighted calculation.

Consistency

Essentially meaning that two elements following the same definition should not show any differences, Consistency measures the coherence of event logs. While content-wise consistency is included in Data Credibility, this part is focused on its syntactic structure, respectively the data's representation.

Verhulst (2016) suggests the following scoring system, which was adapted to take values on a scale from 0-10:

- 0 - Inconsistency in length together with a mix of only string, only digit and string/digit values.
- 2.5 – Inconsistency in length together with a mix of two out of three possible composition possibilities.
- 5 – Consistency in length together with a mix of only string, only digit and string/digit values.
- 7.5 – Inconsistency in length together with only one specific composition.
- 7.5 – Consistency in length together with a mix of two out of three possible composition possibilities.
- 10 – Consistency in length together with only one specific composition.

To apply this scoring system, all non-empty data fields must be checked. Firstly, the average length of the values is calculated. Afterwards, the standard deviation in length is calculated such that a threshold can be set. If a value's standard deviation diverges more than 2 in length from the average, the attribute is considered inconsistent. This threshold can also be set by the model applicant if organization-specific circumstances allow it to be higher or lower. Also, it is checked if only digits are used, only strings are used, or if the data fields consist of a combination of digits and strings. The more inconsistency in these values, the lower the score.

Availability

Described by McGilvray (2021) as Data Coverage, event data Availability can be defined as the comprehensiveness of available data compared to all data of interest. This would lead to a simple calculation of *Available Data / Total Data of Interest*.

Availability can also be defined by the data's uptime (Katukoori, 1995). This measure therefore tackles the system availability and is calculated as *Uptime/ Operating Cycle*

Our suggested approach combines these two ideas which results in the following (AvD = Available Data, DoI = Data of Interest):

$$Availability = \frac{\frac{Uptime\ AvD}{Operating\ Cycle} * AvD}{DoI} * \frac{Retrieval\ Speed}{Optimal\ Retrieval\ Speed} * 10$$

The ratio of AvD to DoI basically represents the level of event data collection an organizational process is on. Nonetheless, there might exist cases in which reaching level 3 is not necessary or wanted. In such cases, DoI can consist of a smaller range of event data, as decided by the process owner. In many cases, *Uptime / Operating Cycle* might be 1.

To extend the definition of event data availability, its retrieval speed can be integrated through a simple fraction of its optimal retrieval speed which is again to be defined by the model applicant. Should the retrieval speed be higher than its optimal counterfeit, the fraction is limited to a maximum of 1.

Timeliness

Event data Timeliness is important because it impacts the relevance, usefulness and reliability of data. Event data that is outdated, lagging, or inconsistent can lead to poor decisions, wasted resources and missed opportunities.

There exist several measures, the most important one being Data Freshness (DF). It is the age of the most recent row in the respective event data table and measured by calculating the difference between the most recent event timestamp in a table and the current system time at the time of freshness calculation. There also exists Data Staleness (DS, measures the time since the target table was most recently loaded (viewed) and the time interval between now and the most recent entry in the table) and Ingestion Delay (ID, measures the time of how long the data pipeline or the ETL (extract, transform and load) process needed to pick the most recent data and load it into the target table).

Due to the availability of timestamps in event data and the time of insertion expected to be missing, only DF is integrated in the Timeliness score. In literature, the approach of measuring data timeliness using Currency and Volatility is widespread (Bovee et al, 2003; Batini et al., 2009).

Timeliness therefore describes, if event data is appropriately up-to date for a specific process. Currency is a measure of how old the information is based on how long ago it was recorded, while Volatility is a measure of information instability, the frequency of change of the value for an entity attribute (Batini et al., 2009). More volatile data therefore needs to be more current to reach the same score in Timeliness. Currency is measured by comparing DF to a maximally tolerated DF specified by the model applicant (DF Tolerance). DF needs to be based on how rapidly event data should be available. Higher currency is therefore better. Should the DF be worse than the DF tolerance (data is less fresh than specified in the DF tolerance), the currency is 0 (no negative values).

$$Currency = 1 - \frac{Data\ Freshness}{DF\ Tolerance}$$

Volatility can be measured by dividing the number of changes in non-empty entries within an event data column by its total number of non-empty entries. A lower volatility is therefore better.

$$Volatility = \frac{changes}{entries}$$

However, we normalize volatility to fit a positively scaled measure through inversion:

$$Normalized\ Volatility = 1 - Volatility$$

An appropriate scaled measure for Timeliness (reaching from 0 to 10), based on Currency and Volatility is therefore suggested to look as follows:

*Timeliness = 10 * Currency * Normalized Volatility*

Timeliness can be calculated for each event data type to detect (more volatile) weak points. In this case, all entries can be included in the same calculation for getting one Data Timeliness score.

Interoperability

This dimension tackles the problem of interfaces. As event data is often generated by various components of an IT infrastructure, its interoperability is not always given. IT often requires standardized formats, communication protocols and data integration tools. One proven method of measuring Data Interoperability is the i-score (Ford et al., 2007). It measures how well different collected data during a process performs regarding interoperability and we believe that this concept can also be applied on the level of log/event data.

Having a certain operational thread modelled in an activity diagram, where each activity should be supported by at most one system, is the base of this measure. Let T be the ordered set of all systems supporting the thread, e.g. $T = \{1, 2, 2, 3, 4, 2\}$, where each number refers to one system. Different (event data generating) systems and their interaction are then modelled in a multiplicity matrix $C = [c_{ij}]_{nxn}$ as a matrix of spin multiplicities where c_{ij} is the number of times a system pair is repeated when the elements of T are taken two at a time in a forward direction. For $T = \{1, 2, 2, 3, 4, 2\}$ as an example, the set of systems taken two at a time is $A = \{(1,2), (1,2), (1,3), (1,4), (1,2), (2,2), (2,3), (2,4), (2,2), (2,3), (2,4), (2,2), (3,4), (3,2), (4,2)\}$. Depending on how often a certain pair appears, the multiplicity matrix C can be defined, resulting in

$$C = \begin{matrix} 0 & 3 & 1 & 1 \\ 0 & 3 & 2 & 2 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{matrix}$$

for this case. Furthermore, a spin matrix S is needed, which represents the intrinsic spins for all permutations of system pairs in the operational thread and therefore its interoperability. S_{ij} is an element from {-1, 0, 1}: the best spin (+1) is assigned when two systems and their generated event data can communicate without any translation, (0) is assigned when intervention is required by another non-human system and (-1) is assigned when the only way for two systems to interoperate regarding log data is if a human system intervenes and translates. S is therefore subject to the specific interoperation characteristics of an organization and could look like

$$S = \begin{matrix} 1 & -1 & -1 & -1 \\ -1 & 1 & 0 & -1 \\ -1 & -1 & 1 & 0 \\ -1 & -1 & 0 & 1 \end{matrix}.$$

Multiplying *C* with *S* leads to the interoperability matrix *M*, in this example

$$M = \begin{matrix} 0 & -3 & -1 & -1 \\ 0 & 3 & 0 & -2 \\ 0 & -1 & 0 & 0 \\ 0 & -1 & 0 & 0 \end{matrix},$$

which helps with the calculation of the final i-score $I = \sum_{i=1}^{n} \sum_{i=1}^{n} m_{ij}$, leading to I = (-6) in this case. Furthermore, an optimal i-score is required, whose calculation relies on every pair spin in S getting set to (+1) except the ones which physically or operationally cannot be upgraded (needs expertise of model applicant). This results in another spin matrix S_{opt} and an optimal i-score through M_{opt} when multiplying it with *C*. Deducting the current i-score from the optimal one results in the Interoperability Gap. Under the assumption that S_{opt} would only consist of (+1), which is however unrealistic, the optimal i-score in this example would be 15, leading to a gap of 21.

Different i-scores can roughly be compared by normalizing them:

$$\textit{Normalized Score} = \frac{Original\,Score - Min\,Score}{Optimal\,Score - Min\,Score}$$

The *Min Score* hereby represents the worst case by using a spin matrix full of (-1) apart from the main intrasystem diagonal in which all values are 1, and the *Original Score* is the achieved i-score. In the example, the normalized score would be $\frac{(-6)-(-12)}{15-(-12)} = \frac{6}{27} = 0.\overline{2}$. To assess interoperability on a scale from 0-10 as with all other dimensions, the normalized score is multiplied by 10. In this case, the final score would therefore result in $2.\overline{2}$. This results in a final *Interoparability* measure:

$$\textit{Interoperability} = \frac{Original\,Score - Min\,Score}{Optimal\,Score - Min\,Score} * 10$$

Supporting Dimensions

While process data quality is clearly the most central predictor for successful process optimization within an organization, it would be insufficient to only increase process data quality to make it work. There are many other influences and indirect dependencies which need to be of sufficient maturity to enable successful process optimization. Existing models suggest many of these dimensions and while the weighting of their importance differs a lot, we consider Governance, Strategy, Technology and Culture to be the most important ones. Assuming that process data quality is sufficiently high, these dimensions can further support or hinder data-driven optimization initiatives within an organization and therefore also need to be considered.

While we focus on putting the central process data quality elements into quantifiable measures, these supporting elements are much less technical and their quantitiative measurement is therefore very hard. Furthermore, as these elements are of less relative importance, a qualitative assessment suffices. Hence, we propose most supporting elements to be assessed subjectively through looking at the suggested subdimensions and their definition explained in the following, before rating their maturity. As for the central dimensions, the assessment of the supporting dimensions should follow a scale from 0 to 10.

Figure 1. *General Structure of the PDQ MM*

Governance

Following the example of Brock et al. (2024) and complementing it with other literature, we consider Governance to be a central supporting dimension which can be divided into the following elements (Martin et al., 2021):

- Digital Methods & Tools Governance
- (Process) Data Governance
- Process Ownership
- Risk management
- Compliance

While *Digital Methods & Tools Governance* tackles the maturity of guidelines that define who can and must use which digital tools and methods, *(Process) Data Governance* discusses the maturity of guidelines for management and control over the use of (process) data. *Process Ownership* tackles the topic of role assignment and accountability by answering the question if there are clearly defined owners for each process and whether they have the authority to make decisions. *Risk Management* describes how well optimization risks are identified, assessed and mitigated, while *Compliance* addresses the organization's adherence to regulatory and internal compliance requirements for process optimization initiatives.

Strategy

Having a strategy as a list of specific, clear actions needed to achieve a high level of digital maturity, is central. At the same time, the digital transformation strategy should not "turn upside down" the existing strategy in the organization, but organically build-in and enrich it, bringing the necessary changes, technologies, and resources for the development and improvement of the organization's performance indicators (Kringelum et al., 2024). Strategy therefore encompasses:

- Alignment with Business Goals
- Scalability
- Innovation
- Resource Allocation
- Strategy Alignment

Alignment with Business Goals discusses to what extent the digital strategy aligns with overall business objectives. *Scalability* represents flexibility and vision, asking how easily the digital capabilities can be scaled to accommodate needs and growth. *Innovation* addresses the extent to which the digital strategy and process optimization can be leveraged for continuous improvement. How financial, human and technological resources are allocated to support the digital maturing is captured in *Resource Allocation*. *Strategy alignment* assesses how well the corporate strategy and digital strategy are connected and complementing each other.

<u>Technology</u>

Especially when applying a maturity model specifically for data-driven process optimization, technological standards heavily influence its success, even when a high process data quality is given (Zhou et al., 2023). This includes:

- Data & Tool Integration
- Performance
- User Friendliness
- Safety
- Privacy

While data interoperability is part of the central dimensions of the PDQ MM, *Data & Tool Integration* is also relevant for other levels and tackles how well the technology is integrated within used systems and data sources in general, not only considering event data. *Performance* describes the systems' capabilities in handling large volumes of data and therefore also includes the modernity of IT architecture. *User Friendliness* is looking at the ease of interaction with optimization tools, also for non-technical users, while *Safety* is assessing established data protection mechanisms. Lastly, *Privacy* is mainly focusing on the amount of deployed de-identification techniques.

<u>Culture</u>

In addition to the three operational concepts Governance, Strategy and Technology, the digital culture within an organization is of great importance for a successful implementation of new technologies deriving from process optimization efforts. It consists of attributes enhancing digital transformation efforts such as taking risks, testing & learning, a no-blame culture, customer centricity, openness to change, agility, autonomy of employees etc. According to literature overviews

(Teichert, 2019, Hartl & Hess, 2017), culture for our purposes can be broken down to the following elements:

- Change Readiness
- Customer Centricity
- Collaboration
- Learning Orientation
- Leadership Support

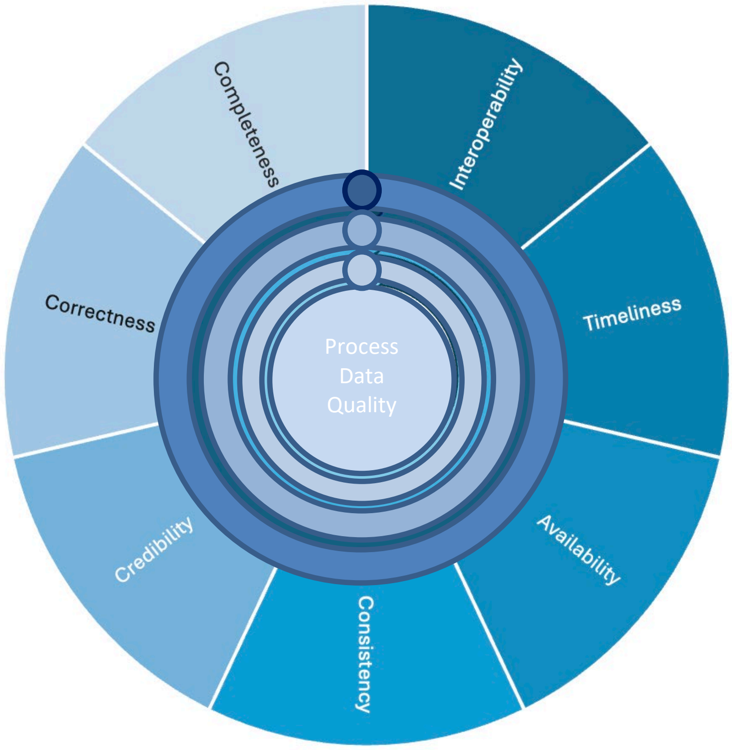
Change Readiness describes the agility and flexibility of organizations as well as having an open culture which is very receptive to change. *Customer Centricity* is essential to keep the value generation and value recipients present and ensure a directed goal-focused usage of digital tools. *Collaboration* asks to what extent employees collaborate, communicate (regarding new optimization insights) and how well they participate. Characterizing an organization by a L*earning Orientation* means that it is innovative and willing to learn from new findings and incorporate them into practice. Essential is also *Leadership Support*, meaning that the management needs to have a "Digital First Mindset" as well as promoting data-improving technologies and showing error tolerance.

Model Summary

The current downfalls of existing models and the emerging suggestions for an improved, more quantitative and far-reaching assessment of digital maturity facilitating the implementation of data-driven process optimization, led to the creation of the PDQ MM.

The central process data quality dimensions are visualized in *figure 2*:

Figure 2. *Overview of Process Data Quality Dimensions*

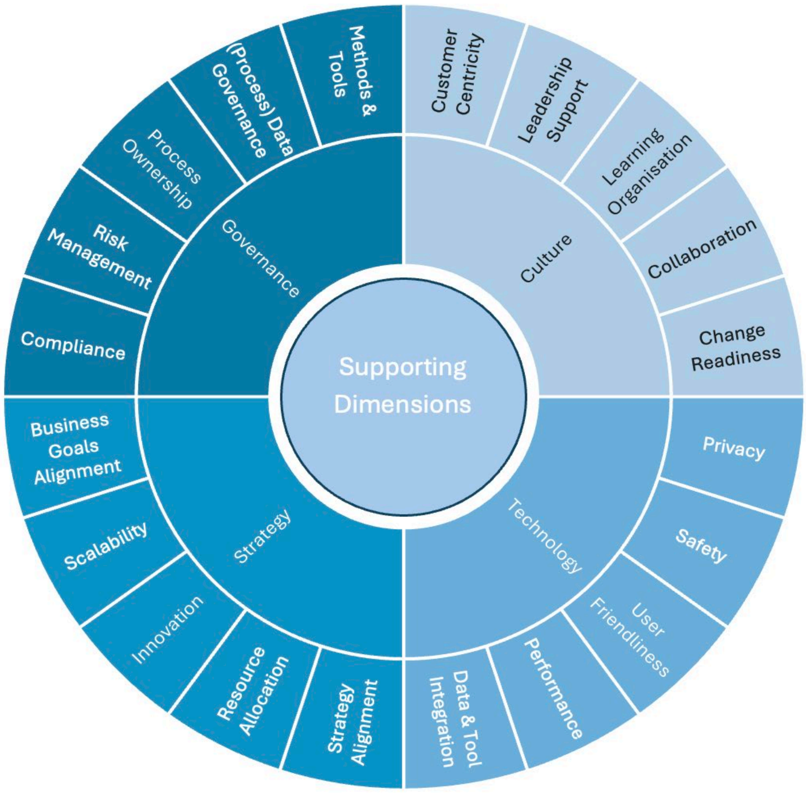


Even though the process data quality dimension is the most central and essential one, the supporting dimensions require some division and specification as well (see *figure 3*):

It is again crucial to bear in mind that the core of the PDQ MM consists of measures of process data quality. While these supporting dimensions can also be assessed by calculating a score on the cale of 0 to 10, this measure is not at the heart of the proposed model. The evaluation of the supporting dimensions is mainly meant to increase awareness of other possible drivers or inhibitors of digital maturity.

Applying the PDQ MM results in both a score for the seven central dimensions as well as the supporting ones. It is suggested to not integrate them into a singular final score but rather interpret them individually to identify different points for improvement.

Figure 3. *Overview of Supporting Dimensions*



Model Application & Discussion

After the PDQ MM development process, its initial application suitability was assessed in a case study, proving its intended strengths and eventually shedding light on potential weaknesses.

Case Description

The PDQ MM was applied to evaluate the digital maturity and process data quality of a financial process in a large Swiss retailing company, focusing on a specific regional unit. This process, standardized across multiple units and implemented on a modern enterprise resource planning (ERP) system, was selected for its critical role in financial operations and its alignment with the organization's digital transformation goals. Data from a defined period was analysed to determine readiness for process data enhancement tools. The process we evaluated is pivotal for handling both internal and external financial transactions. It provided an ideal test case for evaluating data quality and identifying the potential of process optimization to enhance efficiency and decision-making.

Data Preparation and Evaluation

Data Preparation involved extracting event logs from the ERP system, focusing on a key financial document table. The fields *Case ID*, *Timestamp*, *Activity*, *Document Type* and *User* were retained for analysis, while non-essential variables were excluded to streamline the dataset. In the end, 529'787 lines of event data over the five mentioned categories were included in the dataset. Following the defined level classification based on the amount and type of event log entries, the dataset reaches the highest differentiation level (3) explained in Section 4. This assessment represents the first step of the PDQ MM application.

Additionally, qualitative data collection through structured interviews with key stakeholders, including a process manager and a process advisor, was undertaken to assess the critical dimension Credibility, as well as the supporting dimensions. These complementary data sources ensured a holistic evaluation of process maturity.

The seven core dimensions of the PDQ MM were quantitatively evaluated using the standardized scoring methods, while the supporting dimensions were qualitatively assessed to understand their impact on the adoption of optimization tools and techniques. Ratings ranged from 0 to 10, based on the maturity of organizational practices described in *section 4.* The results are presented in *table 2* and *table 3*:

Table 2. *Core Dimension Scores for Example Case*

Core Dimension	Weight	Score	Weighted Score	Remarks
Completeness	0.2	7.7	1.54	Gaps in some secondary data fields
Correctness	0.2	8.5	1.7	Reliable data accuracy
Credibility	0.15	8.7	1.305	Strong support by stakeholder trust
Consistency	0.15	6.5	0.975	Issues with inconsistent activity descriptions
Availability	0.075	10	0.75	Excellent data accessibility
Timeliness	0.075	7.2	0.54	Most data available within a five-minute tolerance
Interoperability	0.15	10	1.5	Process operates entirely within a single system
Final Score			8.31	

Table 3. *Supporting Dimension Scores for Example Case*

Supporting Dimension	Score	Remarks
Governance	7.4	Improvement needed in methods & tools governance
Strategy	6.9	Better alignment with overarching business goals required
Technology	9.9	Excellent system performance
Culture	6.9	Limited leadership support for optimization initiatives
Average	**7.78**	

The final weighted score for the central dimensions is **8.31** on data differentiation level 3. For the supporting dimensions, the average score is **7.78**. These values should be interpreted separately, while the score for the central dimensions provides a more direct indication of the technical maturity for applying digital process optimization (see *section 4.3*).

Comparative Analysis

The PDQ MM findings were complemented by the results from applying the Digital Maturity Model (Bitkom, 2022), revealing different strengths for both models: While the PDQ MM provides detailed, quantitative data quality assessments tailored to the analysed process, Bitkom's Digital Maturity Model offers a higher-level view of organizational digital maturity but lacks specificity for individual processes. Nonetheless, both models resulted in a similar score when standardizing for scale differences, with the Bitkom Model assessing the organization with a score of **3.97** on a scale from 1-5**.**

For this specific case, key alignment areas include strengths in technological infrastructure and process quality, with divergences in data consistency and cultural readiness.

Limitations and Challenges of the PDQ Maturity Model

Despite its strengths, the PDQ MM has notable limitations and challenges that must be considered. One key limitation results out of its inherent process-specific focus, as the model evaluates individual processes rather than providing comprehensive enterprise-wide insights. Even though this is also a big advantage of the model, it necessitates repeated applications across different processes to develop a holistic organizational view.

Another challenge is the time and resource intensity involved. The detailed data preparation and analysis required by the model are labour-intensive, particularly when dealing with large datasets including different systems. Furthermore, the reliance on interviews for qualitative assessments adds to the resource demands.

The model's complexity in execution is also a concern. Even though the quantitative scoring methods for dimensions such as Consistency or Interoperability enable a detailed assessment, they require advanced data analysis skills. This complexity can be a barrier for smaller organizations or those lacking technical expertise, often necessitating external support.

Additionally, there is a dependence on subjective inputs for assessing Credibility and the supporting dimensions. These qualitative inputs can introduce bias and variability, potentially impacting the reliability of the results.

Further, there are scalability issues associated with the model. Its focus on detailed data quality assessments can make scaling its application across all organizational processes impractical without significant automation or tool support. These challenges highlight the importance of carefully considering the context and resources available before implementing the PDQ MM and imply suggestions for further development of the PDQ MM.

Lastly, while the PDQ MM provides a helpful tool to assess readiness for process optimization efforts while also predict their success, the exactly needed degree of readiness, as calculated in the final score, cannot yet be provided at the current stage. Future research and practical application of the model is needed to define a sensible threshold, which should be aspired for process data quality by the model applicants.

Implications for Process Optimization

Despite these limitations, this case application showed that the PDQ MM remains a valuable and decisively more objective tool for assessing digital maturity than current models. Its focus on process data quality provides actionable insights for optimizing processes. Recommendations for future application primarily include the investment in an automated application of the PDQ MM to decrease implementation barriers, reduce manual effort and enhance scalability. Furthermore, combining the PDQ MM with higher-level models, like the Digital Maturity Model, in a hybrid approach could be beneficial for balancing breadth and depth. It is hereby suggested to first apply easier models like the Digital Maturity Model from Bitkom to get a first assessment of digital maturity and then going further into detail with the PDQ MM if the levels of digital maturity and organizational support are sufficient.

Conclusion

The Process Data Quality Maturity Model (PDQ MM) represents a significant advancement in the assessment of data quality within the realm of process optimization efforts. By focusing on both core and supporting dimensions, the model offers a framework that addresses the multifaceted nature of process data quality and the evaluation of readiness for data-driven process improvement. The application of the PDQ MM in a financial process case study underscores its practical relevance, highlighting areas of strength and identifying opportunities for improvement.

However, the implementation of the PDQ MM is not without challenges. The process-specific focus necessitates repeated applications across different processes to gain comprehensive organizational insights. The resource-intensive nature of the model, coupled with the complexity of execution, may pose barriers for organizations with limited technical expertise or resources. Additionally, the reliance on subjective inputs for certain dimensions introduces potential variability in assessments.

Despite these limitations, the PDQ MM offers a valuable and more objective tool for organizations seeking to enhance their process optimization capabilities. By providing a structured approach to evaluating data quality maturity, the model facilitates targeted improvements that can lead to more accurate process analyses and, ultimately, more effective decision-making. Future research should focus on refining the model to address its current limitations, exploring avenues for automation, and developing strategies to integrate the PDQ MM into broader organizational frameworks. Such efforts will further enhance the model's applicability and effectiveness, contributing to the advancement of data quality practices in process optimization.

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