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A Methodological Approach to Prioritize Digital Twin Development in Manufacturing

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ABSTRACT

The digital age has brought about a need for organizations to utilize Digital Twins to improve operational efficiency and decision-making. However, it is difficult for companies to identify and prioritize Digital Twin initiatives that meet the needs of their stakeholders and align with the capabilities of the company and its strategic plans. This paper proposes a methodology for the systematic identification and prioritization of Digital Twin applications in complex industrial settings. The methodology begins by documenting business requirements, current processes, and challenges, and subsequently identifying areas with potential benefits from Digital Twins through the use of an opportunity scoring system. To refine the portfolio of Digital Twin applications to include only those that are impactful and viable, the feasibility of Digital Twin is quantified by evaluating technological (technical capacity and digital skills), organizational, and project risk factors. To validate the proposed methodology, a case study was conducted in collaboration with an industrial partner specializing in injection molding. This real-world application demonstrates the effectiveness of our approach in identifying and prioritizing Digital Twin applications in a complex industrial context. This research contributes to the growing body of knowledge surrounding Digital Twins, providing organizations with a structured approach to leverage the potential of this transformative technology.

1 | Introduction

A Digital Twin (DT) is defined as "an integrated multi-physics, multi-scale, and probabilistic simulation [. . .] and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin" [1]. In simple and broad terms, a DT can be thought of as a coupled virtual representation of a physical asset or system [2]. This enables the simulation, prediction, and optimization of real manufacturing systems and processes to facilitate data-driven operational monitoring and improvement within organizations [3]. According to ISO 23247:2021, the DT concept is a promising approach for cyber-physical integration, offering a range of potential services [4]. Recognizing the value of DTs, organizations are eager to embark on the DT journey. However, many face challenges in identifying and selecting DT projects aligned with their business needs and strategy.

DT implementations are application-specific, that is, they are a fit-for-purpose approach. Developing a comprehensive DT covering all levels of detail is costly, labor intensive, and requires a variety of technologies. This incorporation of various technologies increases the complexity, development time, and resource requirements necessary to design and develop DT applications for industrial practitioners. Additionally, successful operation and

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value creation from DT applications require specialized skills and organizational readiness. Therefore, it is often recommended to prioritize DT applications with the highest return on investment and the best chance of success in the early development stages [5–7]. However, there has been little emphasis on proposing systematic quantitative methods to identify and prioritize those DT applications for target development efforts. Relying solely on intuition during prioritization can lead to misjudgments due to the innovative nature of the DT concept and the scarcity of information [8]. Hence, it is crucial to complement intuition with a systematic method for identification and prioritization.

This paper addresses this critical gap between current research and industrial implementation of DTs. We propose a systematic method to identify and prioritize potential DT applications based on stakeholder needs, technological (technical capacity and digital skills), organizational feasibility, and risk factors. While existing DT prioritization methods focus on individual aspects, our contribution lies in presenting a comprehensive method that assesses stakeholder ratings and multiple feasibility dimensions.

Our method provides a holistic approach that identifies high-potential applications and aligns them with the unique requirements and capabilities of organizations. By considering multiple aspects that affect the feasibility of a DT application, practitioners can make informed decisions about their DT initiatives, ultimately enhancing the successful adoption and implementation of DTs in manufacturing and related domains. Through this innovative approach, we aim to bridge the existing gap in DT research and offer a valuable method for organizations seeking to leverage the transformation potential of DTs in their operations.

Moreover, the development of this methodology is driven by the importance of embracing DTs for companies to maintain competitiveness, since DTs have the capability to support proactive and predictive monitoring in manufacturing system operations [9, 10].

In Section 2, we review related methods for identifying and prioritizing DT applications. In Section 3, we present our methodology to prioritize high-value DTs and support organizations in their ambition to embark on the DT journey. In Section 4, we provide the validation of our methodology at our industrial partner company. Finally, we discuss our method in Section 5 and provide recommendations for future research in Section 6.

2 | Related Work

This section summarizes the main contributions of existing methods to identify and prioritize DT applications. There exist various other methods for prioritizing projects, but our focus is on approaches specific to the DT domain. Table 1 provides an overview of the publications and compares the research contributions with respect to the method that we propose in Section 3.

The study most relevant to our proposed methodological approach is the method of Newrzella, Franklin, and Haider [11] The authors suggested a two-step approach for prioritizing DT applications for initial implementation: (1) quantifying applications with a high opportunity and impact score, and (2) assessing the correlation between data sources and DT applications. This approach can act as a tool for practitioners to identify promising applications from a stakeholder and technology perspective. However, the method does not assess the organizational capabilities required to create business value from DT applications. Further, only the interdependence of DT applications and data are assessed while ignoring other technical aspects such as models and communication infrastructure.

Furthermore, there exist a number of domain-specific approaches. For example, Perno and Hvam proposed a method to identify DT applications in four steps: stakeholder identification, building block definition, physical system selection, and DT development [12]. This framework addresses specific problems in the process manufacturing industry but does not consider organizational factors and digital skills that are required to create business value from the developed DT applications. In addition, Wong et al. proposed a conceptual method to assess individual

TABLE 1 | Overview of contributions of related methods for identifying and prioritizing DT applications.

				Feasibility			
				Technological			
Reference	Scope	Purpose	Opportunity	Technical capacity	Digital skills	Organizational	Project risk
[11]	Product development	App. prioritization	X	X	—	—	—
[12]	Process industry	Project scoping	X	X	—	—	X
[13]	Building maintenance	Task-technology fit	X	—	—	—	—
[14]	Naval sector	Development & deployment	X	X	—	—	—
[15]	Supply chain	Development & deployment	X	—	—	—	—
[16]	Construction industry	Development & deployment	X	X	—	X	—
[5]	Generic	Development & deployment	—	X	—	X	X
[17]	Generic	Development	X	—	—	—	—

Note: References are evaluated for their ability to assess the opportunity and feasibility of a DT application. The feasibility assessment is evaluated with respect to three dimensions: Technological (technical capacity and digital skills), organizational, and risks.

users acceptance and match the DT with the user needs to determine the return on investment in the DT technology at an organizational level [13]. For this purpose, they used the task technology fit model to measure the fit between technology and task. They provide a template to survey potential users about the fit of specific DT services with individual tasks to be performed and map the responses to a task technology fit performance impact matrix. However, this method only evaluates the potential value of DTs from a user perspective without assessing the availability of technology, digital skills, organizational capabilities, and risk associated with the development of DT applications.

Moreover, Vanderhorn and Mahadevan presented a method to explore DT applications by identifying current challenges and the potential impact of DT applications [14]. First, the physical system and its boundaries are selected. Then, levels of abstraction are described to select the required fidelity for models and sub-models. Last, virtual-to-physical and physical-to-virtual interconnections are set up. The main focus of this method is the selection of an adequate level of abstraction for DT applications. However, it does not describe a stringent process for selecting potential DT applications, leaving practitioners with the question of which applications to prioritize when faced with complex processes with numerous activities and complicated workflows. Similarly, Kalaboukas et al. proposed a DT deployment and operation method for supply chain networks [15]. First, the challenges, problems, and areas of improvement are defined. Then, operational process models of different DT application scenarios are created. Finally, stakeholder roles, stakeholder interactions, and data exchange between stakeholders are modeled. The method emphasizes the importance of stakeholder interaction and alignment during DT development to allow value creation through DTs. However, this method does not guide the prioritization process of potential DT applications. Further, Agrawal, Fischer, and Singh developed and validated a method based on the push-pull principle to guide practitioners to select an appropriate level of sophistication in a DT, that is, descriptive to prescriptive, by identifying applications that provide maximum business value (potential impact & required transformation) with technological capabilities being available (models & data) [16]. The method helps in the decision process of selecting DT applications considering technology and business needs, but does not provide quantitative tools nor includes organizational capabilities in the evaluation.

In addition to the academic contributions, two industrial white papers were found [5, 17]. The circular methodology of Deloitte uses six steps to embark on the DT journey. This approach is generically applicable in various environments, aiming to generate the highest value within the shortest possible time [5]. Furthermore, Schalkwyk's approach is based on *The Lean Startup* method using a systematic approach that specifies DT-based solutions given a specific problem with initially vague customer requirements [17]. Both approaches are kept in high detail and address the full DT life-cycle, from identifying applications to monitoring the DT application in operation. However, these approaches do not provide quantitative tools to assess potential DT applications in the early phases of a project.

In summary, there are only a limited number of prioritization methods in the DT domain. The current literature acknowledges this constraint and highlights the importance of methods for industrial practitioners. However, existing approaches lack comprehensiveness, concentrating solely on specific aspects and overlooking the identification of DT opportunities and the assessment of feasibility concerning technological (technical capacity and digital skills), organizational capabilities, and project risk, as shown in Table 1.

3 | Methodology to Identify and Prioritize Digital Twin Application

Our methodology addresses the need for practitioners to focus efforts in DT development. We propose a method to identify promising DT applications from the abundance of possibilities and prioritize selected applications considering both the opportunity and feasibility associated with a DT application.

This approach is grounded in a well-established methodology for developing information systems, which entails comprehensive analysis, design, implementation, and continuous maintenance [18]. We view the development of the DT methodological approach as an integral component of a larger system of systems within the broader engineering landscape. Furthermore, it is imperative to recognize that nearly all systems, including DTs, will soon operate within a larger and more complex environment that surpasses conventional boundaries [19]. This encompasses various domains, including science and engineering, computation and communication, as well as numerous socio-cultural, legal, environmental, and business factors. Therefore, it is crucial to position the methodology for prioritizing and selecting DT applications within an engineering framework that accounts for and integrates socio-technical considerations [19].

Figure 1 shows our approach and situates it within the various stages of a system development process that is typically used in software development projects where the project requirements are not well defined. The proposed method for identifying and prioritizing DT applications involves:

1. Capturing the needs of stakeholders and their current challenges to improve existing processes by assigning an opportunity score derived using the scoring method proposed by Ulwick [20], and briefly describing DT solutions for activities with a high opportunity score.
2. Evaluating identified DT solutions for feasibility using the multi-factor scoring tool presented by Mitchell et al. [21]. The three feasibility dimensions that we proposed specifically for the DT domain, are technological capability (technical capacity and digital skills), organizational capability, and project risk. The outcome of the opportunity and feasibility scoring is a selected portfolio of DT applications that can be moved into development.

The following sections explain these two steps in further detail.

3.1 | Opportunity Scoring for Identifying Digital Twin Applications

Opportunity scoring was introduced as a tool to prioritize efforts in product development [20], and was used to identify DT

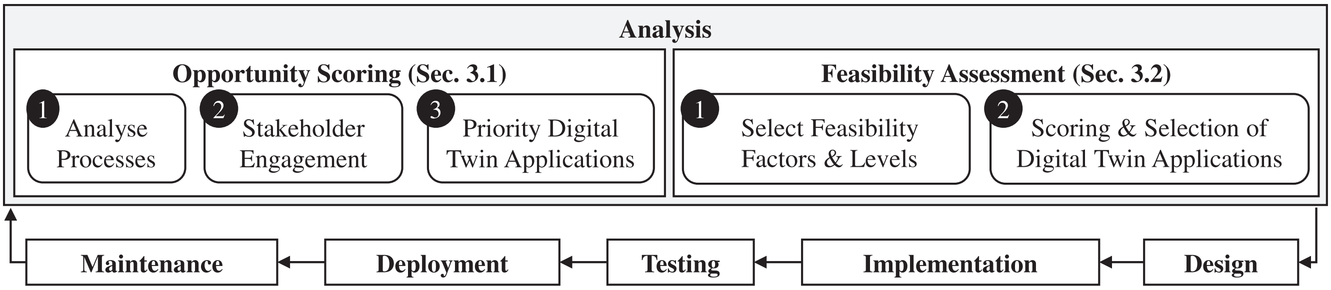

FIGURE 1 | Schematic of a DT development cycle modified from the spiral system development method [18]. The focus of our method is on the initial phases of DT application development that consist of (1) identifying applications using opportunity scoring and (2) prioritizing specific applications using feasibility assessment.

1		2			3
Process(es) & Subprocess	**Outcomes**	**Challenges**	**Importance**	**Satisfaction**	**Opportunity Score**
Process 1.1	Desired outcome 1 of 1.1	Challenges	Importance of outcome 1	Satisfaction with solution 1	Calculated opportunity score
	Desired outcome 2 of 1.1	Challenges	Importance of outcome 2	Satisfaction with solution 2	Calculated opportunity score
Process 1.2	Desired outcome of 1.2	Challenges	Importance of outcome 3	Satisfaction with solution 3	Calculated opportunity score
...	...		...	...	...

FIGURE 2 | Schematic overview of Ulwick's opportunity scoring method [20]. The enumeration in the top of the table indicates the three steps for identifying potential DT applications.

applications [11]. In this methodology, the opportunity scoring method serves the primary purpose of identifying potential activities in a process chain that can benefit from the introduction of DT applications by systematic collection of input from stakeholders. Through assessing importance and satisfaction ratings and subsequently obtaining opportunity scores, the method offers a structured approach to make informed decisions about the potential of DT applications. This approach ensures that the decision-making process is grounded in the insights and perspectives of those most closely connected to the outcomes of the application. A schematic overview of the three steps is shown in Figure 2. Following, the three steps are explained in detail.

1. *Analyzing Existing Processes and Outcomes*: Initially, the existing processes and the desired outcomes of the processes are reviewed. Depending on the organizations level of interest, processes can be further detailed in sub-process steps. Every process and subprocess can have one or multiple outcomes, such as documents, design data, or a physical part.
2. *Engaging Stakeholders: Challenges, Importance, and Satisfaction*: To identify challenges and rate importance and satisfaction, semi-structured interviews followed by quantitative surveys are conducted with stakeholders associated with the process activities. The approach allows for a thorough comprehension of the investigated context through the perspectives of actively engaged individuals. We emphasize the selection of this method, as it aims to derive conclusions from the first-hand experiences of participants within their authentic work settings, thus offering valuable insight into their viewpoints [22]. Stakeholders are asked about two key aspects:
   - Importance: How crucial is the specific outcome to the successful execution of your tasks within the process chain?
   - Satisfaction: To what extent are you satisfied with the way the current solution supports you in achieving the outcome, and what challenges do you observe with the current solution?

   Both responses are rated on a scale of 1 to 5, with 1 denoting low importance or satisfaction, and 5 representing high importance or satisfaction.

3. *Identifying DT Applications*
Based on importance and satisfaction ratings, the opportunity scores are calculated as follows

$$O = I + (I - S)^{+} \tag{1}$$

where O is the opportunity score, I is the arithmetic mean of the individual importance scores, S is the arithmetic mean of the individual satisfaction scores, and the $^{+}$ denotes the *positive part* of the difference between importance and satisfaction. As we are interested in the range of the opportunity, we also calculate the minimum and maximum opportunity scores for each outcome. The minimum opportunity score occurs when the importance is low but the satisfaction is high, and the maximum opportunity score occurs when the importance is high and the satisfaction is low. The minimum and maximum scores are calculated as follows.

$$\begin{aligned} O_{\min} &= \min(I) + (\min(I) - \max(S))^{+} \\ O_{\max} &= \max(I) + (\max(I) - \min(S))^{+} \end{aligned} \tag{2}$$

Then, the process activities are ranked in descending order by their opportunity score. The ranking indicates prioritization strategies to improve the outcome of existing process activities. Activities of high importance, but low satisfaction, are characterized as opportunities to innovate the process. Focusing on these opportunities is likely to improve existing solutions with which stakeholders are currently dissatisfied.

For these opportunities, the challenges identified in Step 2 of the opportunity scoring are reviewed and solutions that take advantage of the DT concept are conceptualized and briefly described. The brief description may contain the scope of the physical entity, the services of the DT application, and the stakeholder-specific value created. These brief descriptions are used in the subsequent feasibility scoring by stakeholders.

3.2 | Multi-Factor Feasibility Assessment for Prioritizing Digital Twin Application Development

Feasibility describes the likelihood that a proposed DT application is realistically achievable and practical. For analyzing the feasibility of the identified DT applications, the multi-factor scoring approach by Mitchell et al. is used [21]. Multi-factor scoring is a two-step process: (1) choosing scoring factors and levels, and (2) completing the scoring and selecting DT applications for prioritized development. In the following, these two steps are detailed.

1. *Choosing the Factors and Scaling Statements*
This section presents the factors that impact the overall value of a DT application in terms of the technological (technical capacity and digital skills), organizational, and risk dimensions. The identified factors are based on a comprehensive review of the available literature, incorporating established and important dimensions from DT competency studies, frameworks, and ontologies deemed relevant to our methodology. We selected the factors for their proven relevance and significance in DT and digital transformation initiatives. By including these factors, we ensure our assessment is comprehensive and aligned with existing literature and industry best practices.
Previous studies have typically examined these aspects in isolation, but our approach involves integrating them comprehensively. Table 2 summarizes and describes the factors in each dimension. Additional dimensions and factors can be added, and the suggested ones can be modified depending on specific DT application and organizational requirements.
We developed the scoring rubrics primarily by using competency indicators identified in the literature on DT and information systems. These studies provide scales that measure the feasibility factors from low to high levels of expertise and awareness. For each factor, a five-point Likert-type scale with corresponding scaling statements is specified. The scaling statements define the meaning of the numerical scaling factors. Each level was coded so that the higher numerical values indicate a greater magnitude of the factors studied. For example, for data availability, factor 1 is equivalent to no available data, and factor 5 corresponds to live data at the required twinning rate. The scaling statements for the scaling factors are summarized in Tables 3–5. In the following, we will motivate the suggested factors and their importance in relation to the feasibility of DT applications.
- *Suggested Scoring Factors for the Technological Dimension*
The technological dimension evaluates a DT application in two main areas: technical capacity and digital skills. Table 3 summarizes the scaling statements for the technological dimension. The technical capacity assesses a DT application's viability, ensuring that the data, models, and infrastructure can support its successful development. This dimension comprises factors related to data availability, model availability, and infrastructure availability.
The digital skills aspect includes a range of skills, both technical (hard) and foundational (soft), related to technology and data concepts. This dimension covers capabilities in data analytics, data literacy, data modeling, as well as considerations around security and ethics. Acquiring the required digital skills can significantly enhance the development and implementation of a DT. Therefore, possessing these skills is essential [48]. Without them, there is a significant risk that organizations might employ individuals lacking the necessary competence to develop and use DT applications [33].
Data availability is the first pillar in assessing the technical capacity feasibility of a DT application. The critical role of data cannot be overstated, as it acts as the central element connecting the physical and the DT system and ensuring physical-virtual consistency [23]. DTs consume various data from several sources such as design and engineering, manufacturing, product quality, and virtually simulated data [24]. Without the availability of relevant data sources and a reliable flow of data, the DT application cannot provide an accurate representation of the current state of the physical system or advanced services. Therefore, evaluating existing data sources and available data update rates are fundamental steps in this assessment.

TABLE 2 | Suggested dimensions for assessing the feasibility of a DT application. The three dimensions are technological (technical capacity and digital skills), organizational, and project risks.

Dimension	Factor	Description
Technological (technical capacity and digital skills)	Data availability [23, 24]	Extent to which the existing sensors and data can support the DT application
	Model availability [25–29]	Fit of existing models of the physical system with the desired objective of the DT or the ability to produce them
	Infrastructure compatibility [26, 30–32]	Availability of infrastructure to process and analyze data, and return feedback to the physical system
	Data analytics [33]	The capability of defining quality requirements for data production and analysis. Proficiency in structuring and analyzing data through statistical analysis and data science methodologies to enhance data understanding
	Data literacy [33, 34]	The capability of displaying proficiency in contextual data creation, utilization, and communication, with a clear grasp of data definitions and methods
	Data modeling [33]	The capability of utilizing a systematic and logical approach for data planning, design, management, and optimization
	Security and ethics [35–38]	The capability of serving as a governing and compliance authority to guide data usage, embracing a secure-by-design approach to cyber-security and business continuity. Takes into account data decisions within the context of business integrity and ethics, while ensuring compliance with data privacy and legal obligations
Organizational	Leadership [33, 39]	The capability to leverage data in order to enhance business operations and cultivate a culture of data-driven decision making
	Communication [40, 41]	The capability of actively listening to others, comprehending data management challenges and requirements, and effectively communicating a persuasive case for improved information management and higher data quality to gain organizational support
	Collaboration [33, 42, 43]	The capability of establishing trust-based relationships to optimize the value of shared data, including models and standards, while acknowledging the broader implications of data asset interoperability
	Learning and adaptability [33, 44–46]	The capability of embracing a learning mindset for ongoing innovation and agile skill development, showcasing resilience when confronted with challenges and resistance to change
Risk	Management commitment [11, 47]	Top management backing of the DT application (initiative)
	Strategic fit [11, 47]	Alignment of the DT application with the organization strategy

Model availability is the second pillar for the technical capacity feasibility of a DT application. DTs require adequate models that can accurately represent the physical systems and perform the computation of the model within the required timescale to return feedback to the physical system [25]. Models in DTs can be classified as geometric, physical, behavioral, and rule-based models [26]. A detailed examination of existing models in the

TABLE 3 | The suggested scoring levels associated with data availability, model availability, and infrastructure availability (technical capacity) and the suggested scoring levels associated to data analytics, data literacy, data modeling, and security and ethics (digital skills) to evaluate the technological feasibility of implementing a DT application.

	Scaling statements				
Factor	**1**	**2**	**3**	**4**	**5**
Data availability	No data available	Limited static data	Dynamic data but inadequate for twinning	Relevant data available for efficient twinning	Rich live data for twinning at required rate
Model availability	No representation available	Representation that lacks details	Incomplete representation	Representation with defined limitation	Accurate virtual representation
Infrastructure availability	No coupling available	Manual data flow	Automatic physical-to-virtual data exchange	Automatic bi-directional data exchange	Real-time coupling for responsive control
Data analytics	Limited ability in scientific methods and statistical data analysis	Awareness of mathematical and statistical techniques	Experienced in utilizing statistical data analysis techniques across diverse datasets	Applies statistical analysis to scale algorithm design across datasets	Leads algorithm design and guides resilient scaling for large datasets
Data literacy	Limited awareness of data and its relevance	Understands the role of high-quality data in decision-making	Generates high-quality data for informed decision-making	Oversees the use of high-quality data for decision-making	Capable of the former, and identifying and recommending improvements in data quality.
Data modeling	Demonstrates limited understanding and ability in utilizing data models	Understands data models and their impact on business processes	Applies data model knowledge to create practical models	Guides data modeling for enhanced sharing and system interoperability	Advises on industry-specific reference data models for automated data interoperability
Security and ethics	Limited understanding and adherence to ethical and legal data standards	Follows ethical and legal data standards	Understands and follows data ethics and legal standards	Sets internal ethical standards and manages non-compliance escalation	Sets best practices, assigns tasks, and ensures legal compliance, governance, and integrity

area examined is required to determine their compatibility with the DT application. Typical engineering organizations already rely on 3D modeling software and other computer-aided engineering software to create engineering models for the design, analysis, and optimization of engineering systems [27]. Assessments should also extend to the adaptability of these models, indicating if updates or modifications are required for use in a DT application. This can result in the replacement of existing computationally expensive model with a surrogate model, for example, using Gaussian process modeling or model order reduction [28, 29]. Assessing the models and the required modification of the model can be challenging in the early stages of DT development, where the DT application is defined in a brief manner. In these cases, it may be necessary to re-evaluate and update the assessment while moving through the system development cycle.

Furthermore, the evaluation of data and model availability must be aligned with each other and with the purpose of the DT. When specifying data sources and data sampling frequencies, consideration must be given to model requirements in terms of required data inputs and update rates. In turn, the model has to fit the desired purpose of the DT application in terms of prediction accuracy.

The third pillar of evaluating technical capacity feasibility is the compatibility of the infrastructure. The compatibility of the infrastructure describes the requirements for having adequate technologies in place to connect DT applications and their physical counterparts [26]. This connection extends to the required infrastructure to collect, transmit, store, and process data, and mechanisms to return feedback to the physical system or the human operator [30]. During the feasibility assessment, attention should be paid to the use of standardized interfaces for data exchange, to ensure that the data can flow smoothly

TABLE 4 | The suggested scoring levels associated with leadership, communication, collaboration, and learning and adaptability to evaluate the organizational capability for implementing a DT application.

	Scaling statements				
Factor	**1**	**2**	**3**	**4**	**5**
Leadership	Limited understanding of data management and digital skills	Values data quality and its vulnerability across process stages	Translates organizational digital vision, securing team support	Identifies and develops digital strengths and areas for improvement	Analyzes trends, plans for future talent needs, and develops skills
Communication	Limited communication skills	Informs team about the importance of improved data management	Expresses the need for quality data management and related challenges	Communicates data management limits and advocates best practices	Explains the “Why” for digital transformation and diverse data tools
Collaboration	Limited collaboration and data sharing	Collaborates across multiple teams	Facilitates data sharing to improve decision-making	Promotes cross-functional data sharing for better decision-making	Role model for an open and sharing culture
Learning and adaptability	Limited ability to learn, exchange knowledge, and adapt	Learns and reflects from personal experiences	Drives knowledge exchange for continuous improvement	Fosters cross-organizational knowledge and idea sharing	Cultivates a culture of continuous learning and builds resilient organizational strategies

TABLE 5 | The suggested scoring levels associated with the management commitment and the strategic fit of a DT application to evaluate the risk of the application.

	Scaling statements				
Factor	**1**	**2**	**3**	**4**	**5**
Management commitment	Minimal involvement and little recognition of the importance	Occasional interest but not consistent support	Management recognizes value and allocates limited resources	Consistent support and active participation	Full dedication and prioritization
Strategic fit	Lack alignment with organizations strategy	No contribution to long term goal	Moderate alignment with defined contributions	Strong alignment with significant contribution	Critical element for achieving long-term goals

between the various components of the DT ecosystem. This standardization not only promotes interoperability between DTs, but also facilitates efficient communication and information sharing within a single DT. Furthermore, manufacturers are collecting increasingly more data throughout the manufacturing value chain from equipment, products, human operators, information systems, and networks [31]. Thus, evaluating an infrastructure's ability to accommodate different types of data, such as structured data commonly found in databases and unstructured data, such as text documents, images, or sensor logs, is essential. A detailed evaluation of data storage and processing capabilities is imperative, as it influences the effectiveness of a DT application in handling a wide range of information. In the cases where the company does not own the computing infrastructure required to process data and run the DT applications, the feasibility assessment should also evaluate cloud computing solutions. Cloud services offer scalability, flexibility, and on-demand resources, which can be a significant asset for a DT application. Evaluation of integration of cloud computing resources into the existing infrastructure framework is essential during the feasibility assessment [32]. Evaluating infrastructure compatibility indicates to what extent the existing information technology infrastructure aligns with the application's requirements and helps to identify potential gaps or areas where infrastructure upgrades or investments may be warranted.

For the second main area of the technological dimension (digital skills), the first factor, data analytic skills, encompasses the ability to collect, process, analyze, and interpret data to extract valuable insights that inform decision making. Individuals with expertise in data analytics employ statistical analysis and various data science methodologies, thus enhancing their understanding of the information derived from the DT [33].

Second, to effectively advance the concept of DT prioritization of the development of basic data literacy skills is essential. Data literacy is defined as the ability to read, write and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques, and the ability to describe the use-case application and resulting value [34]. This is important for effectively developing and implementing DT as it allows individuals to efficiently collect and manage large amounts of data, and use new technologies and tools more effectively, resulting in improved decision-making processes [33].

The third factor is data modeling. Data modeling requires individuals with a systematic mindset who can plan, design, manage, and optimize data flow. They also need a deep understanding of engineering semantics to ensure and effectively manage data sharing and interoperability needed to develop and operate a DT [33].

Finally, ensuring security and ethical considerations is a significant concern in the development of DTs [35]. DTs, being applicable to various scenarios, bring together diverse technologies, data, and knowledge from different areas and departments. This convergence poses unique legal, regulatory, and ethical challenges for organizations, making it essential to assess secure and ethical data handling during the DT development and operation phases. This involves a careful examination of business integrity, ethics, and compliance with privacy regulations and legal obligations, particularly as organizations aim for unified approaches to data sharing [36]. Therefore, organizations must proactively address security and ethical issues throughout the development, implementation, and deployment of DTs. Cultivating a culture of ethical responsibility and accountability at all organizational levels is crucial [37]. This includes establishing clearly defined codes of conduct and ethical principles that outline expectations for responsible behavior and decision-making [49], and ensuring that individuals within the organization comprehend the ethical implications associated with DTs and recognize their role in upholding these standards [38].

- *Suggested Scoring Factors for the Organizational Dimension*

  The organizational capability dimension evaluates the feasibility of a DT application by examining whether organizational and individual skills support its successful development. The importance of organizational capabilities cannot be underestimated. Building a DT includes various aspects that go beyond technology and involve transforming how an organization operates [50]. Therefore, it is essential to ensure that the organization and its employees have the skills required to successfully implement and operate this strategy [51]. The organizational dimension has four factors: leadership, communication, collaboration, and learning and adaptability. Table 4 summarizes the scaling statements of the organizational dimension.

  Effective leadership is key to success in DT. Leaders must drive cultural change, advocate for the benefits of data, and encourage the adoption of the new digital technology [33]. The effective adjustment of an organization to DT depends on leaders who embrace a work culture that integrates digital technology rather than relying solely on it. This also involves developing adaptability to technological advances and making timely decisions regarding the integration of ongoing technologies such as DTs [39].

  Communication is another essential factor for facilitating data and information flow, idea exchange, task coordination, and decision-making in a DT environment. This also involves using digital tools to efficiently transmit data or information while ensuring privacy and safety [40, 41]. Effective communication skills are also crucial to convey the need and importance of transitioning to DT applications, as well as to articulate the potential challenges that can be encountered during this journey.

  Furthermore, the development and operation of DTs require collaboration between various teams with experience in multiple domains. In this context, team collaboration is the collective effort of a group working toward mutual goals, where multiple individuals from different organizational groups pool their resources, expertise, and findings to collectively contribute to the shared outcome [42], being in this case the development, implementation and use of a DT. This fosters optimal use and sharing of data and knowledge. The collaborative approach involved in developing and operating a DT goes beyond optimizing data and knowledge sharing. It acknowledges the wider significance of interoperability, emphasizing the importance of shared understanding and adherence to common standards. This emphasis ensures a smooth interaction and exchange of information among different datasets [33]. Therefore, cross-functional teams (a group of individuals from different functional areas that collaborate to achieve a common goal) are crucial for DT implementation and operation to facilitate the integration and sharing of knowledge while avoiding the creation of new siloed applications [33, 43].

  Lastly, it is crucial that individuals embrace a learning mindset and develop various skill sets to adapt and operate in a DT environment [44]. This ability will allow them to navigate the challenges of an increasingly digitalized work landscape effectively [33]. The utilization of emerging digital tools facilitated by the DT will also empower individuals and organizations to broaden their learning horizons by facilitating the exchange and creation of new insights and ideas [45]. Furthermore, as automation threatens job security, individuals must be agile and resilient in their learning journeys and provide unique value that surpasses machine capabilities. Hence, in light of rapid technological advancements and the overwhelming amount of data generated by DT, it is crucial to possess adaptability and learning skills [46].

- *Suggested Factors for the Risk Dimension*
  Addressing the risk associated with DT applications (as in any other project) is vital for project success. Consequently, project managers are required to perform continuous risk assessments throughout the duration of the project [11]. An effective risk assessment requires a thorough understanding of the types of risks involved and the ability to identify those with the greatest impact on project success. For the development of a DT, we focus on the commitment of management and the strategic fit of the DT application. Table 5 summarizes the scaling statements for the risk dimension.
  Management commitment denotes the support of the DT application initiative by top-level management [11]. This involves managers assessing the required resources and devising a strategy for distributing them in line with the project plan, ensuring their efficient utilization. Moreover, it is crucial for managers to communicate effectively the strategic importance and value of the DT project in order to mitigate any risk associated with change resistance [47].
  Evaluating the strategic fit to understand the alignment of the DT application with the overall strategic framework of the organization is also essential [11]. This alignment entails a smooth integration that ensures that the DT initiative is coordinated with the larger organizational strategy, resulting in a unified and synergistic approach. The absence of proper strategic fit could result in failure to secure user commitment, effectively manage user expectations, and hence may lead to conflict in the organization during the implementation and operation of the DT [47].

2. *Scoring and Selection*
   The DT applications, identified by the opportunity scoring process, are evaluated by a scoring team for feasibility. The scoring team consists of stakeholders with relevant experience and knowledge of the focus area of the DT application. The factors are individually scored by the stakeholders. Then, for each factor, the minimum and maximum score is used to calculate the arithmetic mean minimum and maximum feasibility score as follows

$$F_{\min} = \sum_{i}^{n} \frac{\min(x_i)}{n} \qquad F_{\max} = \sum_{i}^{n} \frac{\max(x_i)}{n} \tag{3}$$

   where F is the overall feasibility score, n is the number of factors and $\min(x)_i$ and $\max(x)_i$ are the minimum and maximum feasibility values for factor i calculated from the individual scores.
   Combining the opportunity and the feasibility score leads to the opportunity-feasibility scoring matrix, as illustrated in Figure 3. The best case (maximum opportunity, maximum feasibility) and worst case (minimum opportunity, minimum feasibility) of the evaluated DT applications are plotted in the scoring matrix. The minimum and maximum opportunity scores are calculated using Equation (2), and the minimum and maximum feasibility scores are calculated using Equation (3). The shown pivot line is one of the possible lines at which the product of opportunity and feasibility is constant. We show a pivot line that passes through the midpoint of the diagram where opportunity equals 2.5 and feasibility equals 2.5 separating the diagram into two regions. These regions approximately represent DT applications that should be moved to development (above the curve) and those that should be paused or require more investigation (below or crossing the curve) [21].
- *Decomposing Feasibility Scores and Managing Dependencies*
  The straight line between the best and worst cases represents the range of possible outcomes for a DT application. A particularly wide range of feasibility or opportunity scores may indicate that there is a lack of information about the DT application. For those DT applications, examining the specifics of the feasibility score, including individual scores for dimensions and factors, can help pinpoint areas that need further development and focus during the implementation of the DT application.
  Our methodology underscores the importance of transparency in the scoring process, offering stakeholders an overview of their maturity across various dimensions and factors. By decomposing the feasibility scores into individual factors, stakeholders can gain insights into the strengths and weaknesses of their current organizational state. Hence, it is essential to assess the dimensions and the factors separately to prevent inter-dependencies. For example, consider a scenario in which the stakeholders rate inadequate infrastructure as low, and data analytics as high due to capable data scientists. The overall feasibility score of the rated applications may be an average feasibility. Further investigation and decomposition of the feasibility score would reveal the dependency issue between these factors, that is, the infrastructure is inadequate to leverage the data scientists' capabilities. Having identified this dependency, the interventions and decision on developing a specific DT application can be planned. Based on this example, we want to highlight the importance of not solely relying on the overall feasibility score but to factor out those individual scores that need to be addressed toward the implementation of a DT application. The overall feasibility score can guide the initial selection of DT applications that are realistically achievable and practical. Thereafter, decomposition in individual factors can help stakeholders to formulate targeted strategies for effectively addressing challenges and prioritizing interventions that are required for successful DT implementation. Therefore, the scoring matrix not only provides information on which DT application should be prioritized for development, but also indicates the level of uncertainty of the application. This enables the identification of uncertainties that cannot be anticipated otherwise and poses a risk of successfully developing and implementing the DT application. The identification of uncertainties supports preparation for the occurrence of those events and the development of an adequate contingency plan.
  For the interested practitioner, we provide a template for conducting the scoring process [52].

4 | Validation Case Study

The proposed methodology was validated through its application to the injection molding domain, serving as an illustrative example. The validation process focused on the analytical phase within the system development cycle. It is important to note that the evaluation did not extend to the subsequent stages of development and implementation, thus refraining from an evaluation of the actual performance of the identified and prioritized DT applications during these later phases. This deliberate focus underscores the utility of the method in the preliminary phases of the system development cycle of DT applications.

The validation was carried out with our industrial partner, which works in the area of injection molding and has more than 3000 yearly active molds. The mold value chain consists of three key activities, mold development, manufacturing, and qualification, as shown in Figure 4. The identification of the three production stages, sub-processes, and process outputs involved a thorough review and analysis that was based on our experiences working within the company under study. We leveraged insights gained from previous interviews aimed at mapping out the various stages and sub-processes within this manufacturing

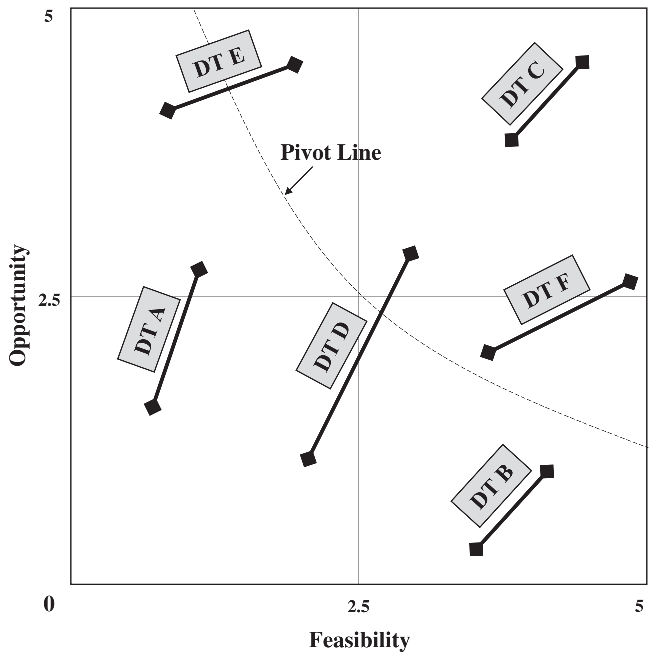

FIGURE 3 | Illustration of an opportunity feasibility scoring matrix [21]. The pivot line separates the DT applications that are potential candidates for focused development efforts from those which should be down prioritized.

environment. Therefore, although our paper does not delve into the specifics of this identification technique, we employed a combination of qualitative methods, including stakeholder interviews, process documentation review, and expert consultation. These approaches ensured that we comprehensively captured all key processes relevant to our study.

The main flow, indicated as **1** in Figure 4, begins with mold development. In mold development, a new mold tool is constructed on the basis of the design of the molded product. The outcome of mold development is a 3D model of the mold tool. Next, in the manufacturing phase, the tool maker prepares the manufacturing instructions and machines the required mold components. The tooling industry typically relies on standardized parts that are purchased externally and only manufactures those parts that directly impact the molded product quality, such as the mold cavity and core. All parts, purchased and machined, are then assembled into a functional mold tool. In the third step, known as the qualification phase, mold construction and functionality are evaluated, and then molding tests are performed to qualify the mold. The mold is then handed over to injection molding.

The production of mold tools is a complex process, and various challenges are encountered. Specifically, our industrial partner faces difficulties as molds sometimes fail to pass through the main flow on the first attempt, leading to delays in progressing into injection molding. This failure results in the need for rework on the mold. The mold is sent back into the value chain for adjustments or repairs, illustrated as **2** in Figure 4. Once all issues are resolved, the mold can proceed back into the main flow, shown as **3** in Figure 4.

Our validation study focuses on these three primary activities in the mold value chain and seeks to improve efficiency by decreasing rework of molds through the utilization of the DT. When developing a new DT application, as in developing any other type of software system, specifying the business requirements improves the understanding of the domain and allows the verification of whether these requirements are reflected during the development and implementation of the DT [53]. In particular, our method aims to meet the following business requirements:

1. *B1: Reduce Rework and Lead Time Throughout the Mold Life-Cycle*
   Today, mold parts require excessive amounts of rework, which in turn increases the time required to bring a new

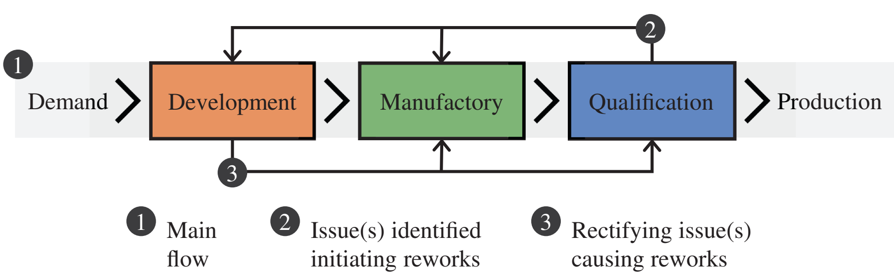

FIGURE 4 | Case study environment at our industrial partner that works in the area of injection molding. The focus areas are element and mold development, mold manufacturing, and mold qualification.

mold tool into operation. The industrial partner believes that an essential element in mitigating reworks and reducing lead times involves knowledge exchange throughout the entire lifespan of a mold tool. For example, information on the functioning of mold's is communicated to the tool makers responsible for producing new mold components and tools.

2. *B2: Increase First-Time Through and Improve Mold Part Quality*
Obtaining the required mold part quality is extremely challenging due to very narrow specifications in the micrometer range and the complexity of manufacturing custom parts in small to single volumes. The industrial partner wants to be able to assess mold part quality from mold development to mold operation to identify and resolve potential quality problems early on.

3. *B3: Enhance Digitization Throughout the Mold Value Chain*
The industrial partner wishes to use digital tools to reduce working silos and facilitate a comprehensive cross-functional understanding of the entire mold value chain. For example, mold designers should better understand how specific design choices affect the complexity of manufacturing and operating a mold tool.

The business requirements **B1-3** serve as guiding principles for the development of DT applications aimed at reducing rework, improving mold part quality, and enhancing digitization throughout the value chain. Following, the focus is on systematically evaluating opportunities for deploying DT applications. This involves scoring and assessing potential areas within the mold value chain where DT technology can effectively meet the identified business requirements.

- *Validity and Reliability of the Survey Instruments*
To ensure clarity and accuracy in our surveys, the survey items were discussed and reviewed with experts in DTs from Aarhus University. Additionally, they were presented at several Digital Twin conferences to gather valuable input and feedback.
We assessed the validity and reliability of our surveys through the application of Cronbach's alpha to determine reliability, and factor analysis to establish validity. It should be noted that our sample size for this study is small, which limits the amount of information provided by the statistical analysis.
To evaluate the reliability of the opportunity scoring survey, we grouped the importance and satisfaction rates by production area (development, manufacturing, and qualification), calculated the averages, and then applied Cronbach's alpha analysis to each group. The values of the Cronbach's alphas for the three production areas exceeded 0.76, meeting the well-accepted reliability threshold of 0.6 [54–56]. This indicates a high level of agreement among the items forming the constructs.
Regarding the validity study for the opportunity scoring survey, we followed the tool introduced by Ulwick [20] and previously used by Newrzella, Franklin, and Haider [11] to identify DT applications. We conceptualized opportunity as a composite of importance and satisfaction and designed our survey to directly observe these concepts. Therefore, factor analysis to test the validity of the opportunity assessment was unnecessary. Moreover, due to high variability across different processes and individuals in various production areas, factor analysis would have been inappropriate and potentially misleading for these specific constructs.
We subsequently performed a reliability and validity analysis of the feasibility assessment survey. Regarding reliability, we determined that Cronbach's alpha coefficients were all in excess of 0.63, denoting an acceptable degree of internal consistency among the items composing the various dimensions.
In contrast to the opportunity scoring, establishing the validity of the feasibility assessment survey necessitated a factor analysis, as the dimensions measured were latent constructs that could not be directly observed and thus required indirect assessment through survey items. For the feasibility assessment, we conducted a factor analysis of our three dimensions to ensure the items for each dimension formed robust and reliable constructs. The organizational and risk dimensions loaded onto a single construct, while the technological dimension loaded onto two. This is logical, as the technological dimension encompasses two distinct constructs: technical capacity and digital skills. Additionally, all factor loadings exhibited the anticipated signs and directions.

4.1 | Opportunity Scoring for Identifying Potential Digital Twin Application in the Mold Value Chain

From the mold development, manufacturing, and qualification stages, sub-processes and their results were identified. The current processes and outcomes were described based on observations from on-site visits, document reviews, and interactions with stakeholders over a span of three years. A total of 14 sub-processes were documented: seven in mold development, four in mold manufacturing, and three in mold qualification. Specific details of the process were not disclosed, as a result of intellectual property agreements.

4.1.1 | Identification of Challenges

To address the above mentioned business requirements, a qualitative approach was used. Semi-structured stakeholder interviews were conducted to identify the challenges that hinder the fulfilment of these requirements. Ten stakeholders were selected based on their level of seniority, years of experience, and expertise in the field, covering all departments in the unit of analysis, that is, the case study environment shown in Figure 4. An overview of the background of the stakeholders and the time of interaction can be found in Table B1. The stakeholder interviews were recorded on video to mitigate the risk of information loss. Throughout the interviews, the stakeholders had the opportunity to express their personal perceptions, observations, facts, and experiences about the challenges they face in their working area. Furthermore, observations during field visits were included as a source of empirical data, helping to create the necessary context for supporting interview data and the organization's documents.

The qualitative data collected in the interviews was analyzed using NVivo, a software program designed to assist in the analysis and organization of extensive qualitative data. Content analysis, an inductive data analysis method, was used to uncover specific challenges from the raw statements collected during the interviews [57]. Initially, the interview transcripts were thoroughly reviewed and open coding was performed to identify key statements characterizing organizational challenges in meeting the business requirements **B1-3** (an overview of key statements can be found in Table A1). This resulted in a list of first-order codes. Through axial coding, these initial codes were compared and refined iteratively, identifying similarities and differences [58]. Similar first-order codes were then grouped into broader conceptual categories (second-order codes), which were further organized into overarching dimensions. The results of this analysis were five main challenges, as summarized in Table 6.

The first challenge (C1) addresses the existence of separated and decoupled systems, as well as isolated units within a company or institution. These decoupled and siloed systems operate independently, without much coordination or information sharing among them. As a consequence, this lack of integration impedes effective communication, collaboration, and decision-making processes, resulting in inefficiencies and decreased overall performance. Challenge (C2) describes challenges related to the quality of parts and elements and involves a wide range of issues that have a direct impact on the final product. These challenges are complex and involve five main factors that can influence both the quality of the mold components and the molded products. The challenge (C3) encompasses a variety of data quality obstacles that obstruct the productivity and reliability of production operations. This challenge takes on various forms and greatly impedes the organization's capacity to extract valuable insights from their data and make well-informed decisions. The fourth challenge (C4) summarizes issues related to process instabilities that pose significant challenges to production operations, which are the absence of robust processes, substantial variations across product categories, and a lack of automation that can lead to inconsistencies in product quality and performance. Without well-defined and standardized procedures, variations can arise at different stages of production, affecting the final output. Lastly, challenge (C5) deals with learning inefficiencies caused by factors resulting from difficulties in capturing and retaining valuable information, lack of traceability, and the risk of losing information. When an organization fails to capture its learning effectively and lacks traceability, the valuable knowledge gained from past experiences remains undocumented and underutilized.

4.1.2 | Rating of Importance and Satisfaction

After determining the challenges, the stakeholders were asked to rate the importance and satisfaction of each process step in the value chain. Figure 5 shows the level of satisfaction of the stakeholders with existing solutions and the importance that the stakeholders assign to the outcomes of the process. In general, stakeholders were satisfied with the current solutions (satisfaction > 3), and most outcomes were deemed as highly important (importance > 3). The findings are interesting because our qualitative analysis shows widespread dissatisfaction with many of the production processes, whereas the responses of the stakeholders in the survey were more positive than anticipated. This could be attributed to the "optimism bias", where the expectations of individuals exceed reality [59].

TABLE 6 | Potential causes identified through the interviews at our partner company within the specific focus area and problem objective. The focus area are mold development, manufacturing and qualification. The problem objective is the high number of reworks in making mold tools.

First order codes	Second-order codes	Challenges
Fragmented data structures	Decoupled systems	Organizational fragmentation (C1)
Siloed work dynamics	Organizational silos	
Surface quality issues	Dimensional challenges	Mold components and molded product-related quality challenges (C2)
Burn, marks, flashes, shrinkage	Visual appearance irregularities	
Dimensions outside specification and missing tolerances	Deviation from dimensions	
Prototype issues not fixed	Oversight of sample errors	
Mismatches between material, color, and tools	Material compatibility	
Several disparate data sources	Unstructured data retrieving	Data quality challenges (C3)
Scattered data	Data handling and utilization problems	
Low-quality and polluted data	Data reliability and validity issues	
Decision making based on experience or gut feelings	Lack of data-based decision making	
Multiple products	Large variation across product categories	Process instabilities (C4)
Manual data retrieval	Lack of automation	
Difficulties anticipating errors	Unforeseen issues	
Reactive performance	Lack of predictability	
Insufficient tracking preventing issue identification	Lack of traceability	Learning inefficiencies (5)
Insufficient knowledge retention	Lack of learning	
Lack of documenting processes and decisions	Information loss	

Figure 5 functions as a roadmap for prioritizing strategies that aim to improve existing solutions or design new ones. The area of the graph is divided into three distinct areas as defined by Ulwick: the overserved region, the optimally served zone, and the underserved domain [20]. In the *overserved* area, innovation opportunities are limited. In contrast, the *underserved* area contains opportunities for innovation, indicating significant unmet needs. These are the opportunities that companies should focus on when developing novel DT applications. Our deliberate focus was specifically on solutions within the DT domain, and we intentionally excluded solutions from other domains.

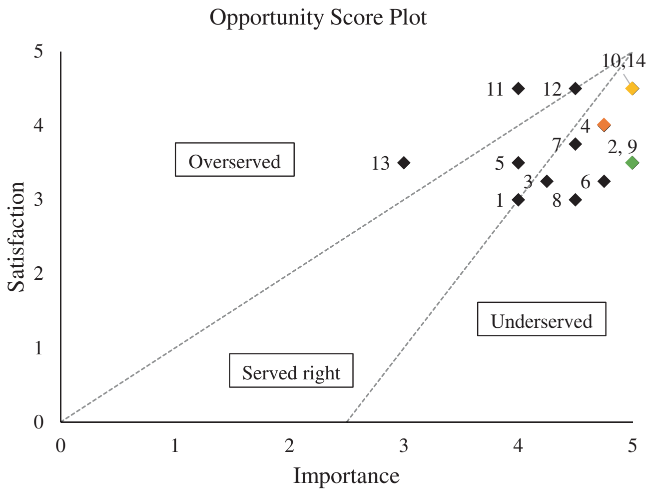

FIGURE 5 | Opportunity scoring results from the case study at our partner company. In total, 14 process outcomes were analyzed. The opportunities that were selected to demonstrate the multi-factor feasibility scoring are highlighted in orange (DT A), green (DT B) and yellow (DT C).

The three opportunities (one for each of the three stages within the examined value chain) with the highest combined satisfaction rating and importance rating were selected as potential candidates for DT development (top right corner and indicated in orange (DT A), green (DT B) and yellow (DT C) in Figure 5). The main reason for this selection is that the upper right corner represents important needs, which are considered key factors essential to developing new competitive solutions [20].

4.1.3 | Ideation of Digital Twin Applications

For these three opportunities, the DT applications were ideated and briefly described in close collaboration between the *Center for Digital Twins* at Aarhus University and the domain experts at the industrial partner company, while considering the business requirements and identified challenges. An overview of the DT applications is provided in Table 7.

The first application (DT A) is related to opportunity (4), located in mold development. This opportunity addresses the challenges mold designers face when performing computational fluid dynamics simulations to simulate molding behavior and optimize mold performance. The behavior of the machine between the same machine brand and type can differ and will change over the lifetime of an injection molding machine. This can

TABLE 7 | Description of the DT applications that were selected for the feasibility assessment by the scoring team. Challenges addressed by the DT application, and the opportunity and potential value are listed.

Code	Idea	Challenges	Opportunity	Potential Value
DT A	Machine specific injection simulation	C1, C2, C5	Mitigate mold design defects by linking data from molding and computational fluid simulation, and enable understanding how changes in molding production and design decision affect mold performance	Advanced simulation capabilities, increase simulation accuracies, and reduction of costly reworks by accounting for machine specific behavior of the molding machines
DT B	Quality assurance in mold manufacturing utilizing machine and process data	C2, C3, C4	Monitoring and on-site identification of part quality to identify dimensional and surface problems due to the complexity of mold components causing reworks, and reduce waiting times due to quality control activities	Detection of performance variations in mold manufacturing, prediction for in-process compensation and reduction of effort and time requirement for quality control activities
DT C	Data-driven qualification of mold functionality and molded product quality	C1, C2, C3	Development of predictive models using molding monitoring data to exchange worn mold parts and service molds before mold performance and molded product quality decrease	Evaluation of mold functionality and prediction of element appearance and metrology using molding machine and process data to enhance mold qualification activities

cause the simulation results to differ from the actual production performance. To account for machine-specific behavior and the change in behavior over the lifetime of a machine, we propose to develop DTs of the specific injection molding machines used in production. Taking into account the unique characteristics of the machine can improve the accuracy of simulation and mold designs, resulting in a reduced number of rework. Specifically, DT A addresses the challenges (C1, C2, and C5). The solution provides mold development with a tool to understand and evaluate the actual impact of design decision on the operational performance of the mold to address the challenge (C1). Furthermore, the DT application can move the otherwise physical tests in mold qualification early in the process and (at least partially) into the virtual space. Therefore, the cost associated with late design changes that are required due to not meeting the required molded product quality caused by mold design and concept can be minimized (C2, C5).

The second application (DT B) is related to opportunity (9) located in mold manufacturing. This opportunity addresses the challenges tool makers face with machining mold components. During manufacturing, the narrow tolerances and complexity of mold components must be considered, especially when producing a small volume of these parts. Today, this process is based on the experience and knowledge of tool makers and post-process quality control activities [60]. To enable on-machine identification of mold part quality, DT B is proposed. This application uses machine and process data from the mold manufacturing process to generate a virtual as-manufactured part. This part is intended to be used for the qualification of the surface finish of the part and metrology and to compensate for quality deviation by optimizing the manufacturing process. DT B addresses the challenges (C2, C3, and C4). The solution provides data-driven means to identify part quality in mold manufacturing addressing challenge (C2), and supports tool makers to adapt data-driven decision tools to improve mold part quality, addressing challenge (C3). Furthermore, the use of DT B has the potential to address process instabilities in mold manufacturing by predicting quality problems and adjusting the manufacturing accordingly to meet this challenge (C4).

The third application (DT C) focuses on addressing opportunity (14) in mold qualification, specifically targeting challenges faced by quality managers in evaluating mold performance and molded product quality. The application aims to overcome organizational fragmentation (C1), mold components and molded product-related quality challenges (C2), and data quality challenges (C3). It proposes a data-driven approach to qualify mold functionality and enhance product quality assessment. Key objectives include organizational integration through a centralized digital twin platform, predictive maintenance models for timely mold refurbishments and maintenance, and the use of molding machine data to evaluate mold functionality and predict element appearance and metrology. By employing these features, the application seeks to detect and rectify issues early in the production process, ensuring optimal mold performance and consistent high-quality molded products. The comprehensive approach of DT C contributes to streamlining the mold qualification process and promoting collaboration among the different stakeholders across the mold value chain.

4.2 | Multi-Factor Feasibility Assessment of Prioritized Digital Twin Applications

The three DT applications introduced above were considered in the feasibility assessment. For the multi-factor feasibility scoring, a structured survey was designed using the factors and scaling statements introduced in Section 3.2. All the surveys involved stakeholders participating in one-on-one online interviews lasting 30 min. Both authors were present during these interviews. One author was conducting the interview while the other took notes and ensured a smooth flow of conversation. We also clarified any doubts or questions raised by the stakeholders.

In our case, the scoring team consisted of the same ten stakeholders who had already been interviewed for the opportunity scoring. First, stakeholder ratings were collected and then using individual scores, an overall average upper and lower feasibility score was calculated using Equation (3). Combined with the minimum and maximum opportunity scores, calculated using Equation (2), the feasibility scoring plot was drawn for the validation case study, as shown in Figure 6.

Based on Figure 6, the three DT applications can be evaluated for their feasibility and opportunity. DT applications A and C are above the pivot line, indicating that these two solutions are potential candidates to be prioritized for further development, while DT B spans a broad range across the pivot line, and therefore more investigation is required to reduce uncertainty before making a firmer decision. As can be seen in Figure 6, the span between the worst and the best case associated with DT B indicates that both the feasibility score and the opportunity score should be reviewed.

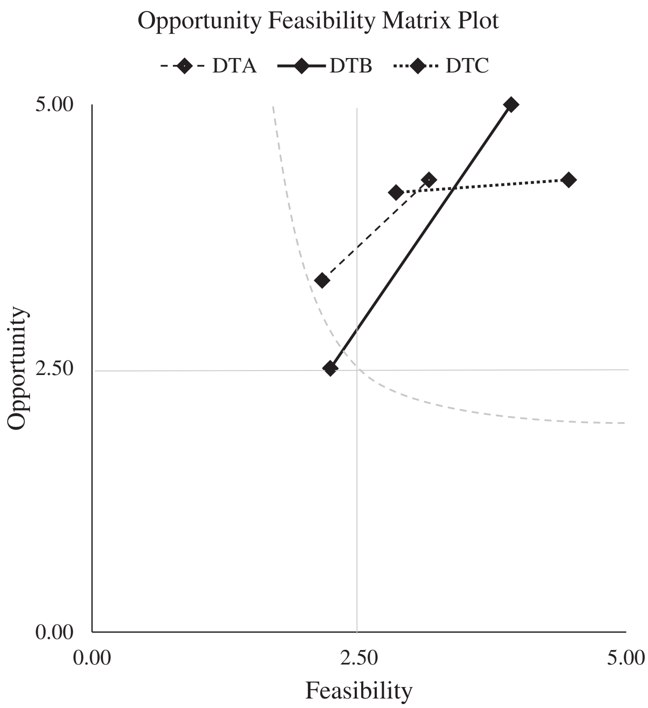

FIGURE 6 | Feasibility scoring plots from the case study at our partner company.

Decomposition of general feasibility into individual feasibility dimensions can provide insight into which factors drive uncertainty in DT B. This information can help identify factors that need more investigation. The goal is to reduce uncertainty and better understand if DT B is a promising application for further development or if it should be given a lower priority. For example, the scoring of the technical capacity and digital skills from the technological dimension shows a broader range between the minimum and maximum score of ≈2 compared to the other feasibility dimensions with a range of ≈1. This may indicate that the stakeholder did not have the information required to adequately rate these factors, and further group discussions could improve the level of certainty of the technological dimension. In this example, we showcased how the opportunity-feasibility matrix can be assessed, emphasizing the importance of considering various factors. It is crucial to note that similar analysis can also be performed for applications above the pivot line, such as DT A and C, to better understand the factors that should be prioritized for project success.

In conclusion, the feasibility assessment performed for the three DT applications provided valuable information on their potential for further development. The structured survey, involving stakeholders and using the multi-factor scoring approach, has allowed for a comprehensive evaluation of feasibility, as described above and illustrated in Figure 6. The results of the validation case study highlight the varying degrees of feasibility and opportunity associated with each application. In particular, DT applications A and C emerge as strong candidates for prioritized development, positioned above the pivot line. However, the nuanced position of DT B, which spans the pivot line, emphasizes the need for additional investigation to address uncertainties and make informed decisions. The decomposition of general feasibility into individual dimensions has proven instrumental in identifying specific areas, such as technical capacity and digital skills, that require further exploration and clarification. This iterative process of evaluation and refinement contributes to a more informed decision-making framework, that can guide the prioritization of DT applications for the subsequent stages of development. As organizations navigate the landscape of digital technologies, this methodology serves as a valuable tool for strategic decision-making, ensuring that resources are allocated to the most promising avenues of innovation.

It is essential to emphasize that the proposed method is part of a larger iterative development cycle that includes repeating the interviews and surveys to refine developed DT applications and identify new opportunities. This iterative approach ensures that feedback and insights obtained from applying our methodology are consistent.

5 | Discussions and Conclusions

This paper proposed a systematic method that enables practitioners to identify and prioritize potential DT applications based on the needs of stakeholders and the feasibility of the application. There are a limited number of approaches to analyze potential DT applications. However, these methodologies are not comprehensive, consider only individual factors in their assessment, and lack quantitative and systematic tools. We introduced a methodology to help practitioners identify activities in existing processes that can benefit from the implementation of a DT application and evaluate those applications in terms of their feasibility. We suggested 13 factors to assess the feasibility of a DT application in relation to four dimensions that are technical, organizational, digital skills, and project risk. Furthermore, we conducted a validation case study that included ten industrial experts and 11.5 h of interaction in collaboration with our industrial partner, specialized in injection molding. In this case study, we analyzed 14 process outcomes to see if they could benefit from a DT, and performed feasibility scoring for the three opportunities with the highest combined importance and satisfaction scores. The results indicated that our method is applicable in a complex, real-world industrial setting and provides systematic and quantitative tools for practitioners to identify potential DT applications and prioritize the development of a selected portfolio of DT applications.

Our method is based on existing research on DT and digital technology applications, extending and refining previous approaches to identify and prioritize DT applications [20, 21]. We addressed key research challenges, including the lack of systematicity, the absence of quantitative decision-making tools, and a narrow focus on individual factors.

Additionally, our method proposed a comprehensive feasibility evaluation that incorporates various perspectives to guide decision-making processes and improve the probability of success in DT application development. We suggest factors from multiple domains, evaluating technical aspects like models, data, and communication infrastructure; organizational readiness and workforce capabilities; and project risks. It is important to note that the feasibility score is calculated by averaging the factors within each dimension. This approach is chosen because the number of factors varies across dimensions. Averaging the factors will help to ensure a fair and equitable assessment of feasibility across all dimensions. However, when considering the average scores from the feasibility assessment alone, it is important to recognize that valuable qualitative details may be overlooked. A single average number might not provide enough information. Therefore, our approach emphasizes transparent scoring processes in order to give stakeholders a comprehensive view of their maturity across different dimensions and factors. Breaking down the feasibility scores into individual factors allows stakeholders to understand both the strengths and weaknesses of their current organizational state.

Within our framework, generating ideas for applications of DT requires a specialized knowledge base, typically from an expert group in the DT domain. This expertise may not always be readily available. Recognizing this potential limitation, we advocate the creation and incorporation of a standardized template with our method during the DT application conceptualization. This template can function as a structured guide and may enhance the ideation process of DT applications, particularly beneficial for individuals who lack an extensive background in DTs.

It is essential to acknowledge that our proposed methodology serves as an initial prioritization framework for DT applications. The method employs importance and satisfaction scores to map the organizational landscape, guiding initial focus and effort allocation. However, our overarching model, inspired by the iterative nature of software development processes, emphasizes the necessity for continuous refinement. Therefore, subsequent iterations require revisiting the initial assessment and reassessing the importance and satisfaction rating. At present, these ratings appear to be relatively high, possibly because stakeholders have become very familiar with and habituated to the understudied processes, underscoring a current limitation of our study and thus emphasizing the requirement for additional iteration and refinement. This iterative approach ensures the inclusion of continuous improvements and the smooth adjustment to any unforeseen changes, thereby promoting a flexible and adaptable implementation plan. Furthermore, to consider future implications in our model, during the feasibility analysis we evaluate not just the present condition but also the level of readiness or unreadiness of various stakeholder groups for future developments, such as the integration of DT technology. Therefore, the feasibility analysis serves as a forward-looking component of the methodology, providing insights into the feasibility and viability of implementing DT solutions in the context of anticipated future needs and challenges. This enables stakeholders to make informed decisions about prioritizing DT development efforts based on their readiness to capitalize on future opportunities, mitigate potential risks and process inertia.

In summary, our methodology contributes to the ongoing efforts to bridge the gap between DT research and industrial implementation. The method provides a systematic and comprehensive approach that combines stakeholder ratings to identify potential DT applications and feasibility scoring of these potential applications in terms of technological (technical capacity and digital skills), organizational, and risk factors. This methodology can guide the decision making of practitioners with quantitative information to effectively identify and prioritize DT applications, minimizing uncertainty while maximizing the likelihood of profitable outcomes.

6 | Future Research

The findings of this study point to the need for further research and discussion on the following aspects:

- *Extending Validation Scope*: The proposed methodology was validated in collaboration with an industrial partner that is active in the injection molding industry, and with a selected number of stakeholders. The results indicate that the method provides the quantitative means to assess potential DT applications and determine areas that require additional attention when progressing to the next stages of development. Even so, there exist a number of other fields that can benefit from the adoption of DTs and thus broadening the scope of validation is required, first within the manufacturing industry and then in other domains.
- *Assessing Stakeholder Perspectives*: Further improving our method in terms of usability and proposing best practices on how to apply the method requires input from stakeholders, including end users, decision makers, and industry experts. For example, the theoretical model for evaluating Information System design methods developed by Moody [61], which is based on the Technology Acceptance Model, can be used to assess the views of stakeholders on factors such as actual efficient and effectiveness, perceived ease of use and usefulness, intention of use and actual usage of the method.
- *Evaluating DT Applications Throughout the System Development Cycle*: Our validation case study deliberately focused on the analysis phase of the system development cycle. However, it is imperative to monitor and compare the performance of identified and prioritized DT applications as they progress through the system development cycle. This can help to determine whether our method actually prioritizes the right DT applications and where adaptation to our method is required to improve the selection process.
- *Assessing the Risks of not Implementing a DT Application*: In the future, we aim to incorporate an additional dimension and factors that account for potential negative effects or risks associated with not implementing digital technologies such as DTs. The adverse consequences of missing out of major trends such as digital transformation can be observed in well-known companies such as Kodak and Nokia [62, 63]. Our goal is to include factors such as diminished market attractiveness, innovation deficit, and loss of competitive advantage.
- *Strengthening Survey Instruments with Increased Sample Size*: In future iterations, we plan to increase the sample size of our study to enhance the validity and reliability of our survey instruments. By doing so, we aim to derive more robust and comprehensive insights, which will strengthen our findings.

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Disclosure

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

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Appendix A

Interview Quotes

The Table A1 summarizes key quotes from the expert interviews. These quotes helped to identify the root causes listed in Table 6.

TABLE A1 | Quotes from the interviews with domain experts.

Organizational fragmentation (C1)	
Decoupled systems	"There are a lot of different kind of data in different systems" (B) "The data sources are different the architecture of the data is different. So it would take forever to clean the data and make correlations" (A) "We have various departments that can do several things (. . .) and it can be often a challenge to get actually the data (. . .). It is just a bit disjointed" (F)
Organizational silos	"We have troubles with collaboration. A lot of trying to solve by themselves and not together with other departments" (H)
Mold components and molded product-related quality challenges (C2)	
Dimensional challenges	"The common issues are dimensions and surface quality issues" (D)
Deviation from dimensions	"Dimensions are many times falling outside the specifications" (E) "Once we measured, the dimensions are not according to specifications" (G) "Dimensional things are found outside specifications. We tend to deviate a lot" (D) "We have a wide range quality issues, some of them to do with the standards" (A) "Measurements that we have are slightly out of specification" (A) "High quality standards, which are good, but makes everything more demanding (. . .) and more challenging" (B)
Visual appearance irregularities	"We have issues with the wrong tolerances, missing dimensions, burns marks, flashes, and shrinkage" (H) "I think the worst we have is mostly scratches on the elements and flashes. That is a common quality issue" (I)
Oversight of sample errors	"When we have an issue, if I look to the prototype and it has the same marks (that the inspected mould), then they might has forgotten to solve the problem" (I)
Material compatibility	"There is a challenge with the new materials, sustainable materials, coming in, which is a way to force us to make a compromise, especially in the visual part" (G) "Sometimes we can not see which color the element is to run in and can not find it (. . .). We need to be sure we have standard colors to run (. . .). We need to be sure because sometimes you need to optimize in the special color because sometimes is the color setting the limits" (I)
Data quality challenges (C3)	
Unstructured data retrieving	"If the person in charge does not sum it up correctly (a meeting) then all these data are worthless" (I). "The data is not very structured. We have a lot of sources and a lot of things happening in many places, but they are not structured (B)"
Data handling and utilization problems	"It is usually difficult to find all data if you want to see certain information. It is not very easy" (G)
Data reliability and validity	"The reliability of the data is the main challenge. Because maybe we can look and see the measurements of the mould, but can we really trust that to make good and valid decisions on how to proceed" (C) "Sometimes I think we base our decisions in not so valid data" (C) "We have too much polluted data" (E) "Validity of the data, that we can actually trust the data, that it is clean, it is a challenge" (A)
Lack of data-based decision making	"Many times when you do quality assurance or quality control, the input is based on opinions and feelings and experience and maybe not always on data" (C) "There is maybe not one way of doing stuff but there are many ways of doing them. So it can often become a matter of opinion" (C)
Process instabilities (C4)	
Large variation across product categories	"We have 25 or something different product categories" (D)
Lack of automation	"We have a lot of different systems that we need to update manually. We don't have a many automized ways of doing things, so we need for example to copy the same information into three or four different systems to make sure that other areas around us can access this information. Then you need to do it in several different places and you do that manually" (C)
Unforeseen issues	"One of the things that we do rework on is actually things that we could not really foresee because it is really hard to foresee what happens" (C)
Lack of predictability	"The output performance is only reactive. You can only react on what you have because it's already too late" (A) "We are unfortunately only reacting retroactively to mistakes" (B)
Learning inefficiencies (C5)	
Lack of traceability	"We do not have a good traceability. If you want to conclude that a wrong material or new material have an issue, then you need to have traceability in place" (E)
Lack of learning	"It is a bottleneck in our processes that we do not learn. Maybe people learn on their own from mistakes. But this is not learning that is captured" (D)
Information loss	"Someone would fix an issue on their own and they would not record that they have made a mistake. They would fix it. So this is data that are lost that we do not see" (E) "If it does not result in a change (. . .) some of the data can be lost" (F)

Appendix B

Interviewed Experts Profile

Table B1 summarizes the expert profiles and the time of interaction with each expert.

TABLE B1 | Expert profiles interviewed for the development of the DT mold system framework.

Code	Background	Total hours of interaction
A	Senior Engineering Manager	30 min (semi structured interview) + 30 min (surveys)
B	Program Manager	30 min (semi structured interview) + 30 min (surveys)
C	Senior Manager	30 min (semi structured interview) + 30 min (surveys)
D	Director	60 min (semi structured interview) + 30 min (surveys)
E	Quality Manager	60 min (semi structured interview) + 30 min (surveys)
F	Senior Mechanical Engineer	30 min (semi structured interview) + 30 min (surveys)
G	Senior Element Qualification Engineer	30 min (semi structured interview) + 30 min (surveys)
H	Senior Quality Engineer	30 min (semi structured interview) + 30 min (surveys)
I	Senior Moulding Process Enginer	60 min (semi structured interview) + 30 min (surveys)
J	Senior Program Manager	30 min (semi structured interview) + 30 min (surveys)

Note: Overall, 11.5 h of interaction with 10 experts.