Social Media Perspectives on Digital Twins and the Digital Twins Maturity Model

Jim Scheibmeir and Yashwant Malaiya

Abstract Digital twins are virtual representations of their physical counterparts. Digital twins help us model, monitor, and predict physical things. The digital twin concept and implementations are frequently discussed on social media platforms. This chapter offers an analysis of the varying conversations of Digital Twins on social media, specifically the Twitter platform. Social media offers a platform for sharing information that can be analyzed to extract valuable information. Social media records can be analyzed to evaluate the velocity, volume, and variety of data related to a specific topic. Industry mentions, use cases, and sentiment of the associated topics and network graphs are introduced as well as supporting background information. The analysis reviews over 24,000 tweets collected between September of 2019 and July of 2021. We have identified the most mentioned industries with interest in Digital Twins. Among identified trending topics, the top three include the Internet of Things, artificial intelligence, and industrial uses. A maturity model for digital twins is introduced, informed by the identified trends and their popularity. The significance of the findings is discussed.

1 Defining Digital Twins

The digital twin concept has many definitions and contributing authors. Jones et al. (2020) attribute Michael Grieves, along with John Vickers, with the origination of the concept. According to Rosen et al. (2015), the digital twin concept's roots come from NASA's Apollo program, twinning a spacecraft for training and mission support purposes. The term "digital twin" was coined by Shafto et al. in 2010 (Shafto et al. 2010). Grieves describes a digital twin as consisting of a physical asset, its virtual representation, and a two-way connection (Grieves 2014). Grieves is a commonly cited author and includes in his definition of a digital twin the existence of a bi-directional virtual to physical connection. The CIRP encyclopedia definition does not include a virtual to physical connection in its description. Tao et al. extend the

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original three-component model by Grieves, the physical, virtual, and bi-directional connection between them, to one having five dimensions: the physical environment (PE), virtual environment (VE), services of both, the data of the digital twin, and the connection (Tao et al. 2018). Eckhart & Ekelhart do not define digital twins as having control over their physical counterparts (Eckhart and Ekelhart 2019). Rather they focus the definition and capability of the digital twin toward monitoring, visualization, and prediction. In their research of identifying definitions of the digital twin, Negria et al. (2017) found that the digital twin's definition has varied and diverged away from solely modeling a physical system. Implementation definitions also range from digital twins being an augmented reality (AR) application to machine learning models (Schroeder et al. 2016). The amount and timeliness of integration that is required for a virtual instance to be considered as a digital twin have not been agreed upon. Eckhart & Ekelhart do not specify that a digital twin should secure the physical counterpart unless that is a part of the optimization. Digital twins can aid in the security of the physical counterpart using different access models and malicious activity identification techniques (Scheibmeir and Malaiya 2020). Eckhart & Ekelhart have suggested characterizing the digital twin concept based upon the level of data flow, integration, and autonomy. Other characterizations toward defining a digital twin include simulation, assisting with a physical system's operational health, and optimizing a system process (Haag and Anderl 2018; Glaessgen and Stargel 2012; Uhlemann et al 2017). The common difference among digital twin definitions is whether the digital twin should control its physical counterpart.

Digital twins increase the digital touchpoints of a cyber-physical system (CPS) and offer hackers knowledge of system integrations (Hearn and Rix 2019). Many digital twin integrations are with devices commonly referred to as the Internet of Things (IoT) technology. IoT has improved the management of homes, businesses, industries, and public sectors (Girma 2018). The information security concerns of IoT range from authorization, authentication, privacy, and access control of embedded systems. In general, IoT technology has produced a new cyber-attack surface (Atalay and Angin 2020). A study on consumer IoT, smart speakers, identified enjoyment (34.24%) as the most influential reason for the adoption of the devices (Arpnikanondt et al. 2020). While IoT consumer devices may offer enjoyment, they must also be secured.

While enjoyment is a major contributing factor to IoT adoption among consumers, miniaturization, and technology price decline have attracted Industry 4.0. Industry 4.0 is the convergence of modern manufacturing and modern computing. Smart factories are building smart devices. If, or when, a smart factory is exploited, the supply chain of smart devices may generate exponential security concerns.

To mitigate new threat vectors, a multi-model of security access controls can help the digital twins secure their physical counterparts. Multiple security models within the digital twin act as filters that trap malicious behavior before the physical assets executing the instruction. Control instructions, current, and predicted future states can be compared across the physical and virtual systems. Discrepancies can imply an inaccurate digital twin or indicate malicious acts. However, codified rules and advanced analysis techniques within system operations will not be enough to deter and prevent all risks and exploits. Security must start with the organization's culture in a bottom-up approach (people, processes, and system inception to retirement).

Social and cultural issues and complexities exist in the implementation of digital twins. Frequently, this is related to the types of data being collected, stored, and exposed by the digital twin. Digital twins have been used by device producers to understand how product use differs across cultures and locations. Even a local sports team's home game schedule can be a factor in modeling and predicting factory production.

Cybersecurity is not the only concern when implementing digital twins. Current standards and architectures for IoT, a technology that informs a digital twin, do not solve their interoperability problems (Novo O and Di Francesco 2020). Organizations contributing to IoT standards include the World Wide Web Consortium (W3C), the Internet Engineering Task Force (IETF), the Internet Research Task Force (IRTF), OneM2M, and the ETSI Industry Specification Group for cross-cutting Context Information Management (ETSI ISG CIM). Progress in IoT standardization includes these example services and protocols:

- A Thing Description is a file containing semantic metadata about an IoT thing including its properties and behaviors
- Resource Directories are repositories of things and their network identification
- Constrained Application Protocol (CoAP) offers device communication over UDP and other transports. A CoAP datagram is illustrated in Fig. 1.

The first two bytes of a CoAP datagram indicate the version of the protocol. Version is followed by two bits indicating the type of the message. The type of message could include confirmable, which requires acknowledgment of receipt. Acknowledgment becomes another message type. The token length field indicates the length of the upcoming token field. The value of the token field is used to connect request messages to their responses. The message identification field can be used to identify duplicate messages as well as to match an acknowledgment to a confirmable message. After message options, a byte of all one's indicates the start of the message payload. CoAP messages are asynchronous and use unreliable transports such as UDP but offer mitigating features such as retransmission of confirmable messages (Shelby et al. 2014).

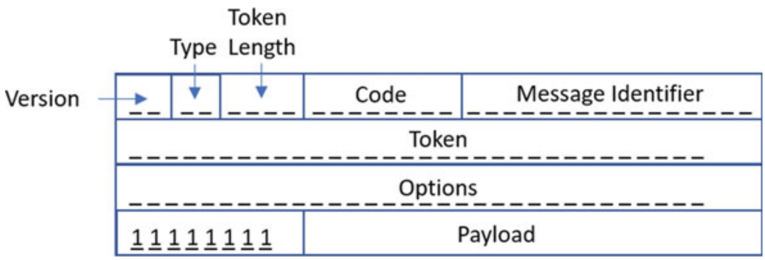

Fig. 1 The message format of constrained application protocol

Standards and interoperability among devices are important because a digital twin may have a lifecycle many decades long. During such a span of operations, many IoT devices that are informing the digital twin may be swapped in and out due to failure, enhancement, or upgrade. The lifecycle of a digital twin requires affordable and feasible interoperability of IoT devices. IoT devices should be reusable, discoverable, and adaptable. These attributes of IoT devices help a digital twin to become maintainable.

To evaluate performance and scalability, tools such as CoAPBench may be utilized to evaluate implementations. The CoAPBench employs virtual clients that simulate IoT device registrations. CoAPBench can scale many concurrent clients while measuring response times from the management layers of an IoT and digital twin system. For a digital twin to achieve the characteristic of fidelity, or sameness to its physical counterpart, many IoT devices will be integrated and informing the digital twin solution. Non-functional characteristics, such as the performance and maintainability of the system will be critical in the management of the digital twin over an extended lifespan. Characteristics such as reuse and discoverability of IoT endpoints will help accelerate the maintenance and enhancements of digital twins over their lifespan.

A development model and methodology for using APIs for digital twins have been put forward (Scheibmeir and Malaiya 2019). The development model begins with an objective tree and contextual diagram to cover the environment, relationships, and operations of the physical entity. The development of a digital twin must encompass the functionality of the physical counterpart, supporting and foundational data sources and integrations, as well as the context of the operating environment and culture. Using context diagrams and objectives trees are methods to explore and define the needs of a digital twin.

Test-driven development was suggested as a practice for implementing APIs in a test-first approach. Utilizing OpenAPI specification aids design and test documentation and supports reuse. Traditional software development lifecycles place testing the system after its development. A better approach is to "shift left" and test during the design and development through practices such as Test-driven development and Behavior-driven development. These practices focus on the creation of unit tests and UI tests before any code being implemented. With these practices, testing comes before code development work and thus "shifts left" in a traditional development cycle.

Performance engineering for digital twins must be done early, such as testing individual parts or components of the API operations. Testing for performance concerns early in the development helps avoid expensive redesign efforts. Figure 2 is from the 2019 work of Scheibmeir and Malaiya and illustrates the use of contextual diagrams, objective trees, TDD, and many more practices in the development of APIs for digital twins. The model suggests API mediation but fails to extend into concerns for the user interface. Augmented reality has been suggested as an interface modality for digital twins.

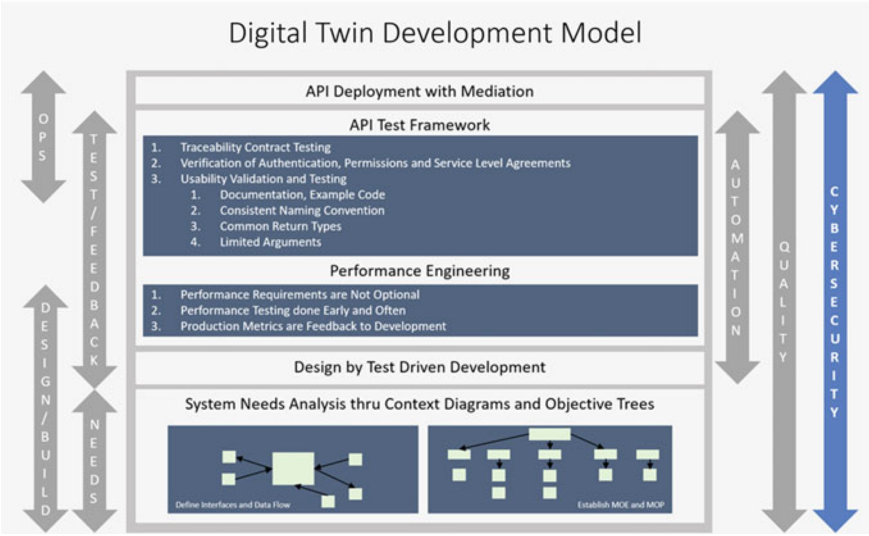

Fig. 2 A framework for developing APIs for digital twins

2 Use of Social Media Analytics in Research

Social media data is common to many research investigations. Social media data is publicly available and offers velocity, variety, and volume of data. Researchers can extract valuable conclusions from social media due to its public nature and ease of access (Cruickshank and Carley 2020). Twitter data has enhanced biased survey populations and assisted in research by aiding in the latitude and longitude of where conversations take place (Martin et al. 2020). A study by Bougie et al. found that 23% of tweets by the software engineering groups they followed were toward software engineering topics (Bougie et al. 2011). Of that 23% of tweets, 62% were toward solving software engineering problems. Software engineering practitioners use social media platforms to learn about technology trends (Storey et al. 2010). They do not cite scientific research in their blogs (Williams 2018). Beyond trend identification, social media platforms offer links to web resources, networking people, and directing our attention (Büchi 2017). Searching for and accessing information are the leading factors among college students for accessing social media platforms (Gómez-García et al. 2020).

2.1 Social Media Analytics Methodology

Utilizing R programs and the Twitter API, we have collected (not exhaustively) 24,275 tweets between August 2019 and July 2021. This is not a comprehensive collection of all tweets referring to digital twins. Our collection of tweets is limited by unpaid access to Twitter's API and further constrained by daily limits and the R programs collecting tweets toward many different topics. While the analysis is limited, it informs on the public discourse about digital twins and our methodology will be discussed in enough detail to enable similar research for those who want to dig deeper in this area.

A content-based analysis is utilized within this research to determine themes among the tweets. Themes may include technology trends or industries where digital twin technology is frequently discussed. Time series analysis indicates ebbs and flows of the discussions and helps identify when peaks or lulls in the discussions are occurring. Sentiment analysis provides a numerical approach to how positive or negative the meaning of a tweet's language may be. Network graphs help identify relationships. This chapter will utilize network graphs to detect relationships between the industry discussions of digital twins and which technology trends are included and omitted from the discussion. When confronted with large amounts of free-form text, it may be useful to utilize clustering techniques to determine the distinct topics and conversations occurring. The cluster sizes are determined by the within-cluster sum of squares (WSS) and the average silhouette methods. A dendrogram is a data visualization object and a type of tree graphic. Dendrograms depict the closeness or sameness of objects after they have been clustered. These methods are useful when analyzing social media and other data sources and will be utilized throughout this chapter.

2.2 Time Series Analysis of Tweets About Digital Twins

Twitter supplies a created date field that identifies when Twitter users posted their communication. The earliest tweet within our collection was posted on August 29th, 2019. The last tweet in our collection is dated July 31st, 2021. Figure 3 is a time series chart identifying the date the tweets from our data set were posted to the Twitter platform and the number of tweets per day. A smoothed line is positioned along the time series to indicate the overall trend in the volume of tweets.

The chart identifies a peak in the discussions of collected tweets during January 2020. To determine the trends driving up this peak, we isolate by the posted date and identify tweets having the highest retweet counts. Retweets are a feature and behavior among Twitter users who can repost a tweet to propagate the message through their network. Within the January 2020 peak period of digital twin tweets, a tweet by Stephane Nappo was the most retweeted with eighty retweets (Nappo 2020). The tweet's message is like many of the definitions reviewed earlier in this chapter and describes a digital twin as a virtual model that can bridge the physical and digital worlds. The image represents a virtual replication of a city. Smart cities are a popular form of digital twins. The tweet utilizes many hashtags, such as #AR

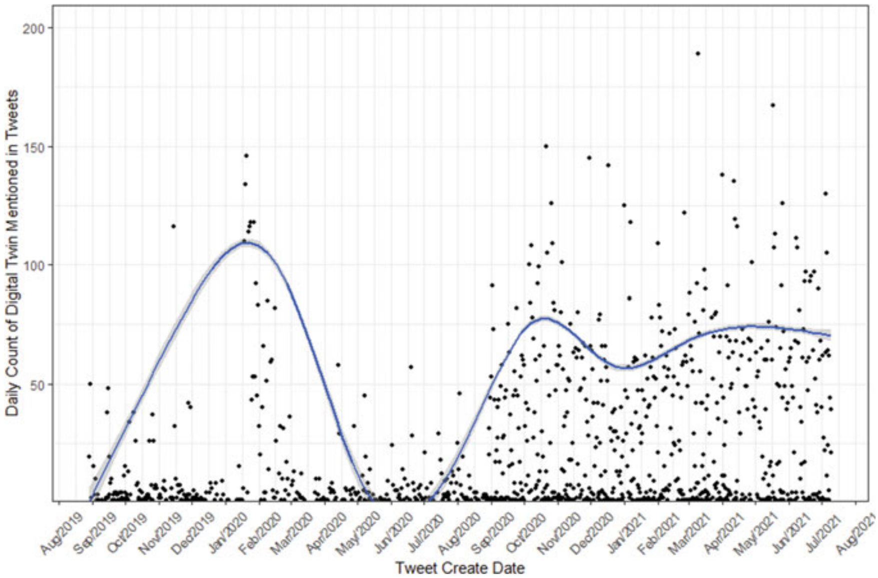

Fig. 3 Time series chart of our collection of tweets referring to digital twins with a peak in January of 2020

(augmented reality), #IoT (Internet of Things), and #AI (artificial intelligence), that draw Twitter users' attention and help gain more attention to the tweet based upon platform algorithms.

2.3 Unsupervised Clustering of the Digital Twin Tweets

We utilize a document term matrix as input into an unsupervised cluster analysis. The document term matrix is a large object that contains an identifier of each tweet, the words used within the tweet's text, and the frequency of the words. The clustering algorithm searches through the document term matrix and groups the tweets based upon patterns in the utilized words and their frequencies. To determine an appropriate number of groups, or clusters, to be created, we utilize the within-cluster sum of squares (WSS) and silhouette methods. There are other methods that can help with clustering and determining cluster sizes, such as DBSCAN, HDBSCAN, or gap statistic methods (Burkov 2019).

The WSS method will iterate through generations of clustering incrementing the number of individual groups with each generation. During each iteration, the squared distance between all the observations within the cluster and its center are summed. This is done for all clusters and the total WSS is then compared with the other generations each having an increasing number of clusters. The ideal number of clusters is frequently determined visually, known as the "elbow method." The

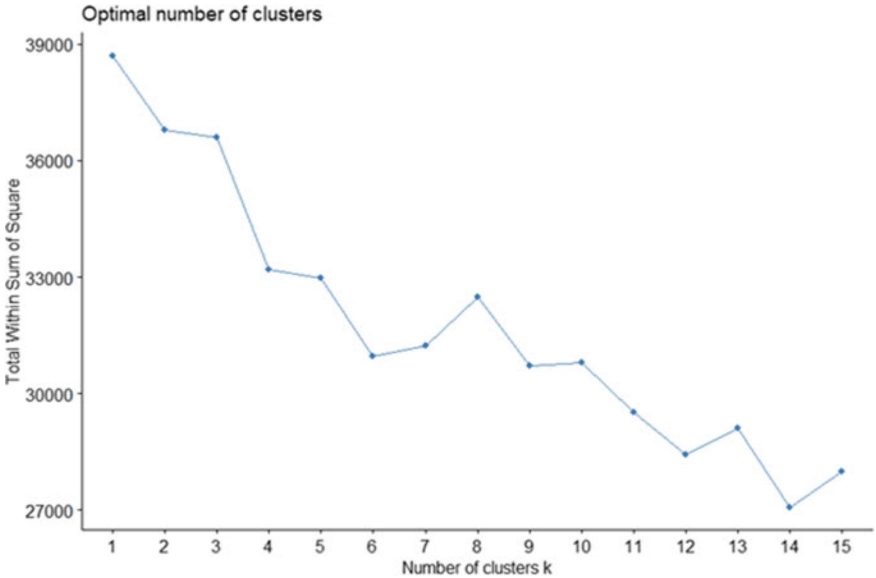

Fig. 4 Within-cluster sum of squares indicates that the proper number of clusters, identified as "elbows" in the line, maybe two, four, or six groups

"elbow" is visually identified when the WSS decreases rapidly in initial generations of smaller n number of clusters and the decrease flattens as n increases. The WSS output is plotted in Fig. 4 with a few potential "elbows" in the line occurring at two, four, and six clusters generated.

The silhouette method also strives to find the proper number of clusters in a collection of data. The method is like the WSS method in that it will iterate through generations of cluster creation and compare each generation. The comparison is performed across the distance between observations in a cluster and observations in the neighboring cluster. If many clusters exist within a small dimension, observations will be near neighboring observations, and this may indicate that too many clusters have been generated for the dataset. We utilize R libraries of nbclust and factoextra to quickly implement the WSS and silhouette methods. The output of the silhouette method is found in Fig. 5 and identifies four clusters as the appropriate amount for our collection of digital twin tweets.

Another helpful data visualization graphic when performing text analysis and hierarchical clustering is the dendrogram. Dendrograms are tree-based graphics that indicate relationships. Dendrograms are frequently created when observing the distance between observations in document term matrices and help visualize cluster distribution. The problem with dendrograms is that they do not scale well when the number of observations approaches many thousands. In these cases, the graphics become either quite large or very densely populated making discernment difficult. Because dendrogram diagrams do not scale well with large observations, we have cast only a

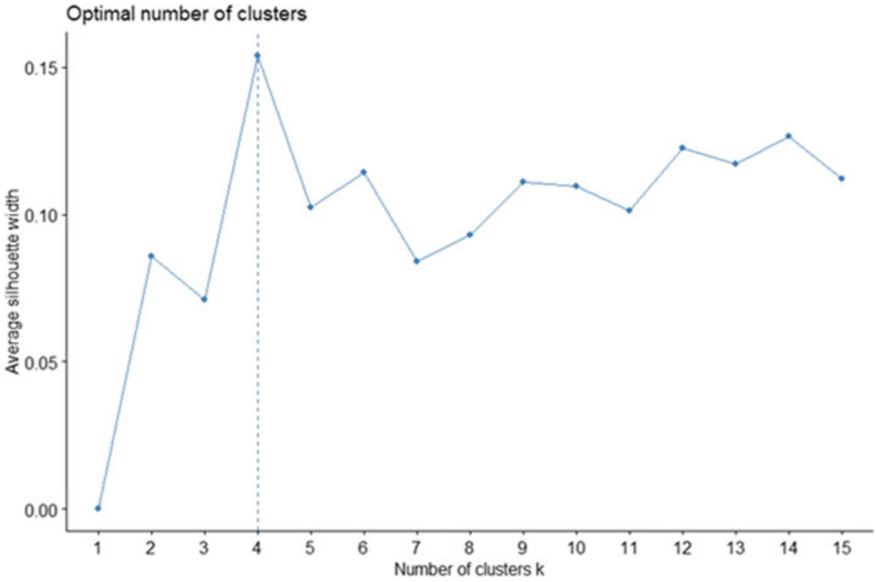

Fig. 5 Average silhouette method indicates four clusters as the appropriate grouping size for our collection of tweets

sample of 1% of our 24,000 tweets. Dendrograms can be customized with specific visual formats such as the typical tree diagram and circular and in our case, we are utilizing the phylogenic shape. Phylogeny is the development of traits or taxonomic grouping. It can help discuss biology and the evolution of species. Here, we utilize a phylogenic dendrogram to illustrate the evolution of the conversations within the digital twin tweets, illustrated in Fig. 6.

Trends were extracted from the four clusters by the frequency of mention. The largest cluster in the volume of tweets is the first group, magenta in the phylogenic dendrogram (only a sample of 1% of tweets were used to generate the graphic), and the top seven trends by mention come from this first cluster:

- the Internet of Things
- Artificial Intelligence
- industry use
- collaboration
- the virtual world
- novelty
- data.

The remaining three clusters then provide three other trends to round out the top ten: machine learning, blockchain, and augmented reality. The largest cluster of tweets is displayed by word cloud in Fig. 7, further illustrating many of the top trending concepts.

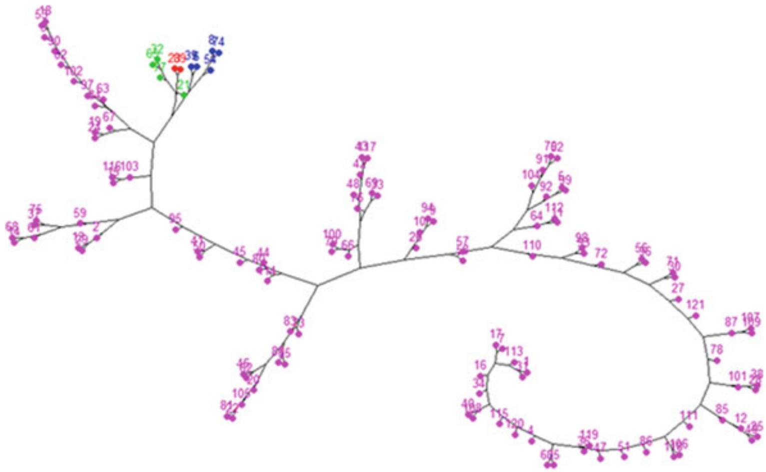

Fig. 6 Phylogenic dendrograms can be created using distance calculations from document term matrices but dendrograms do not scale well with large numbers of observations

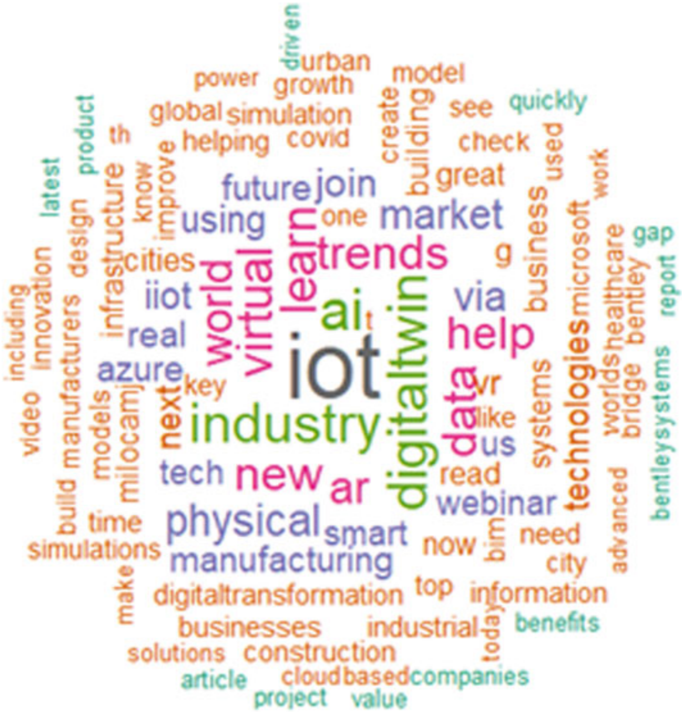

Fig. 7 Word cloud graphic of the most frequent terms from cluster one

Tweets can be retweeted by users to further promote the message content. The most retweeted post from the first cluster of tweets references technology predictions by Global NTT (Rai 2019). Digital twins are one of the emerging technologies that the predictions include. The tweet's embedded link is to an online article that summarizes the predictions and mentions that digital twins can collect data from instrumented assets, model behavior, identify patterns, and create more accurate conclusions (BW Online Bureau 2021).

From the second cluster, the most retweeted post references the 44th episode of IoT Coffee Talk, an online webinar by Tiffany (2021). This tweet merges business concerns such as the conversion of manual, human-driven, or paper processes into optimized and automated processes via digital transformation. These technologies may improve the efficiency of industry and consumer behaviors to also solve sustainability concerns. Some of the hashtags in the tweet by Tiffany are like those within the most retweeted tweet of the first cluster, #AI, #AR, and #DigitalTwins (Rai 2019). However, Tiffany introduces additional trends in his tweet including 5G, edge, cloud, sustainability, and digital transformation (Tiffany 2021).

The most retweeted post from the third cluster is again a reference to trends and predictions, this time the trends listed were identified by the research and advisory organization, Gartner. The tweet links to an article that identifies eight trends in three categories with two additional cross-cutting trends. The three categories include Intelligent, Digital, and Mesh. Digital twins are identified as the fourth 2019 technology trend by Gartner (Panetta 2021). The article by Panetta further states that digital twins have:

- robustness in their modeling profile to support business outcomes
- link to physical assets to potentially model and control
- drive new business opportunities when big data analytics and AI are applied
- interaction to help evaluate future states such as modeling and simulation.

The most retweeted post in the fourth cluster offers some distinction from the previous three (RolSOuLi 2021). This tweet references an open-source distributed ledger system that is like standard blockchain but utilizes a different algorithm requiring less energy (Ullah et al. 2021). Because IOTA can run on devices having less computational power and bandwidth, it enables the value and security of distributed ledger in the realm of IoT devices. The tweet mentions the tangle algorithm, which is used by the IOTA distributed ledger and could be utilized to secure digital twins by creating more trust in the IoT ecosystem.

2.4 Twitter Analysis by Industry

Content-based analysis of the tweets has identified the mentions of specific industries. The International Labor Organization maintains a curated list of industries and descriptions (International Labor Organization 2021). This curated list can be utilized in a labeling algorithm to identify industry mentions within the tweets. The health

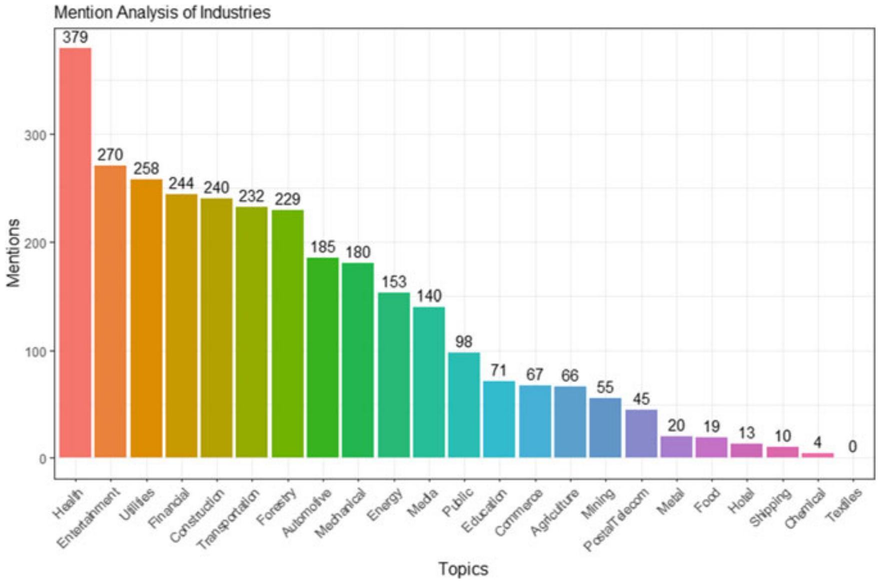

Fig. 8 The health industry had the most mention within the collection of digital twin-related tweets

industry is the most mentioned within this collection of tweets, followed by entertainment and utilities. The textile industry was not mentioned within our collection of tweets, illustrated in Fig. 8.

Considering the sentiment and emotions that are prevalent in the tweets is an interesting research angle. Sentiment analysis typically reviews content on a continuum of negative to positive. Our sentiment analysis will review the tweets by industry and for specific emotions that may be felt or influenced by the message of the tweets, including sentiments such as anticipation or fear among others. This analysis will utilize the NRC lexicon to label the tweet's sentiment.

The labels having the most tweets were the health and entertainment industries (shown in Fig. 8). It is more probable that a tweet using words that convey anticipation will reference the health industry (31.0%) compared to the entertainment industry (8.7%). The naïve Bayes algorithm was utilized to determine these probabilities. The formula for naïve Bayes is explained for our classification problem and data set in Eq. 1.

The naive Bayes equation explained

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{1}$$

where

$P(A|B)$ Probability of *industry* mention given a specific *sentiment*
$P(B|A)$ Probability of *sentiment* given a specific *industry* in mentioned

$P(A)$ Count of *industry* observations divided by total number of observations
$P(B)$ Number of instances of a *sentiment*, divided by all observations.

To calculate these probabilities, we may start with the numerator, which is the product of the probability of positive sentiment given a specific industry and the probability of a tweet having a relationship to the same specific industry. This example will focus on the sentiment of anticipation (it has many observations) and the health industry as it was identified as having the most labeled tweets. Table 1 identifies the sentiment factors across all industry classes and will inform our formulas for the health industry.

In this training data set of the classification model, 780 tweets reference health and within those tweets, 157 have the sentiment of anticipation. The conditional probability of anticipation sentiment (*B* in Eq. 1) given an agricultural tweet (*A* in Eq. 1) is presented in Eq. 2:

Conditional probability of positive sentiment given a tweet references the agriculture industry:

$$\begin{aligned} P(\text{Anticipation}|\text{Health}) &= 157 \div 780 \\ P(\text{Anticipation}|\text{Health}) &= 0.201 \end{aligned} \tag{2}$$

The conditional probability of anticipation sentiment given a tweet referencing health is 20.1%. To complete the numerator, we need the product of the $P(B|A)$ and the a priori, or the number of health-related instances divided by the total number of size in the data set. Equation 3 determines the a priori.

The a priori is the probability of a tweet referencing health and is found by dividing the count of health instances by the total training data set count.

$$\begin{aligned} P(\text{Health}) &= 780 \div 3411 \\ P(\text{Health}) &= 0.229 \end{aligned} \tag{3}$$

The numerator is divided by the probability of a tweet having the sentiment of anticipation. This is determined by dividing the number of anticipation instances for all classes (507) by the total amount of training data instances (3411). Probability of a tweet having the sentiment of anticipation is determined in Eq. 4.

The probability of the sentiment anticipation occurring in the data set

$$\begin{aligned} P(\text{Anticipation}) &= 507 \div 3411 \\ P(\text{Anticipation}) &= 0.149 \end{aligned} \tag{4}$$

The posterior or the probability of a tweet referencing the health industry if we know that the message contains the sentiment of anticipation can be determined using Eq. 5.

The probability a tweet's message is referring to the health industry given the sentiment includes anticipation

Table 1 Counts of sentiments by classes of industry

Industry	Anger	Anticipation	Disgust	Fear	Joy	Negative	Positive	Sadness	Surprise	Trust	Totals
Agriculture		13		1	11		42			8	75
Automotive	1	1		1	1		8			8	20
Commerce		20		2	6	5	46		3	19	101
Construction	7	25	2	7	11	11	165	1	4	56	289
Education	3	18	1	2	11	2	62	1		16	116
Energy	2	9	1	2	21	6	75	2	1	29	148
Entertainment		44		50	38	45	137		43	3	360
Financial	6	22	1	7	17	4	80		11	33	181
Food	2	6			4	1	8			4	25
Forestry	10	33	4	10	30	7	120	3	9	64	290
Health	18	157	4	137	14	11	255	19	3	162	780
Hotel		2			3	1	5	1		3	15
Mechanical	1	5			7	3	22		2	10	50
Media		4					6			1	11
Metal	1	2		2	5	1	14		2	1	28
Mining	3	4		5	7	4	47		2	21	93
Postal/Telecom		4			8		30		7	8	57
Public	1	23		7	7	5	49		2	8	102

$$P(\text{Health}|\text{Anticipation}) = 0.310 = \frac{0.201 * 0.229}{0.149} \quad (5)$$

These equations could be performed a second time with the numerator updated for the entertainment industry to prove the statement, given a tweet has the sentiment of anticipation, there is a greater probability that the tweet references the health industry (31.0%) compared to the entertainment industry (8.7%).

Given a tweet references the food industry, there is an 8.0% probability that the sentiment of the tweet will be anger. The probability of the sentiment of trust occurring is highest for the industry of automotive; however, automotive referencing tweets only convey trust with a probability of 40.0%. The sentiment of disgust is rarely found in the tweet messages, and the highest probability of disgust was found in messages labeled toward the industry of forestry (1.4%).

The R library e1071 offers a naïve Bayes function that eases the implementation of the algorithm. Unfortunately, given the quantity of data we have, and the factors supplied to the model, we only achieve an accuracy of 25.5%. To increase the accuracy of this model, first, increase the number of tweets in the collection and, second, improve the factor selection beyond only utilizing the factor of sentiment.

Network graphs visually identify relationships. Within the analyzed conversations, not all industry-related tweets reference the top trends. Tweets that reference the food or hotel industries have very little relationship to trends. This is visible in Fig. 9, a network graph where the industry nodes are yellow, the trend nodes are green, and the relationships between these labels are red lines. The construction industry tweets are the most inclusive to top trends.

3 Background on Maturity Models

While we have noted the many definitions of the digital twin, determined popular industries in the public discussion, and uncovered the sentiment in the conversations, we have not uncovered what a good digital twin is. To help organizations determine the level of value, and to further improve and enhance their development process, we suggest a digital twin maturity model.

Maturity models help organizations achieve capability and capacity within a discipline or process (Mittal et al. 2018). To increase the capability or capacity, an organization first places itself along a trajectory that is determined by current performance (De Jesus and Lima 2020). Achieving a state of greater capability along the same course becomes the goal. A maturity model establishes the milestones of capability and the distance between current and goal states.

Assessments of maturity inform organizations and their leadership teams about their current capability and readiness. Organizations frequently utilize a questionnaire to place their competencies or system capabilities along the path of the maturity model. These can be self-assessments or utilize consultants. The questions and the

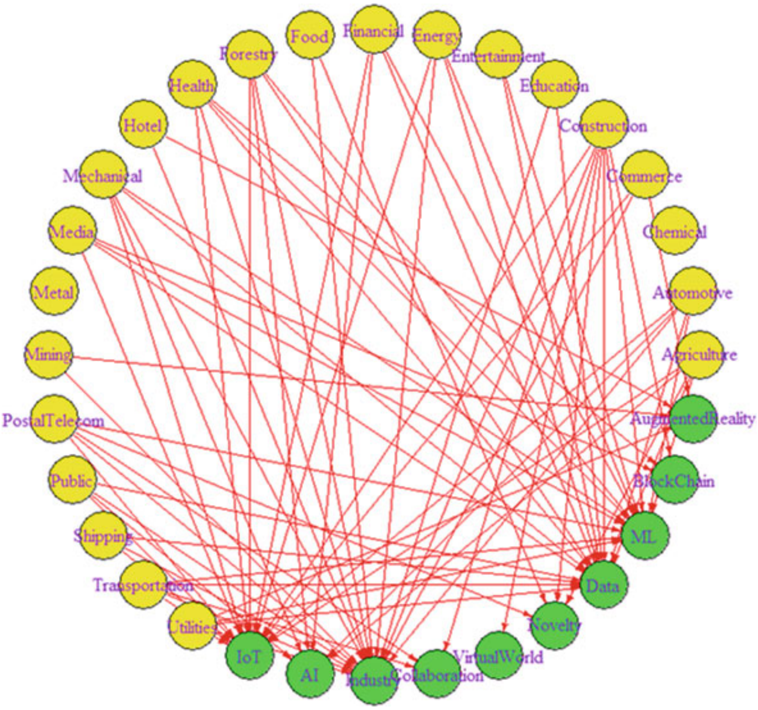

Fig. 9 This network graph illustrates the relationships found in tweets between industries and trends

maturity model assessment effort evaluate Key Performance Indicators (KPIs) to position the organization and system capabilities.

Organizations have two options when requiring a maturity model. The first option is to apply a generic model, and the second option is to build a specific and contextual model to a problem domain. To build a specific model, five factors must be considered: context, conceptual characteristics, interaction with experts, the use of surveys, and qualitative research.

4 The Digital Twin Maturity Model

The creation of a maturity model for digital twins requires defining the benefit that would come from using the model. Kluth et al. describe a maturity model as a representation to evaluate business processes (Kluth et al. 2014). Kohlegger et al.

describe a maturity model as one that represents distinct stages of increasing capability (Kohlegger et al. 2009). A maturity model for digital twins is a tool and associated process to measure increasing and distinct milestones of value derived from a digital twin by its capabilities.

After defining the benefit, the next step in creating a maturity model is to determine the characteristics and parameters of digital twins for distinction along a path of increasing system capability or capacity. Some foundational and general parameters have been established; governance, supportive technology, connectivity, value generation, and competence of the organization (Colli et al. 2018). Dimensions of maturity models frequently include high-level concerns of people/culture which includes the skills, organizational structures, and processes, as well as technology (Cognet et al. 2020).

A digital twin maturity model can be informed by existing models for Industry 4.0. Industry 4.0 describes the integration of people, objects, and equipment to allow flexibility and autonomous decision-making in manufacturing (Agostini and Filippini 2019). Industry 4.0 can be described as a transformation from predominantly mechanical to predominantly digital manufacturing (Oztemel and Gursev 2018). Given a digital twin is of a factory, it would be integral to Industry 4.0. Digital manufacturing is aided by these technologies and principles (Bakkari and Khatory 2017):

- Changeability—The manufacturing equipment and product will evolve, requiring a capacity for change.
- Decentralized Decisions—Smart factory systems are composed of smart machines. Smart describes the optimal condition of equipment making decisions autonomously. Although autonomous, smart systems may be informed by centralized data sources, control units, or human workers.
- Interoperability—When such change to the system or environment occurs, components will require updating and enhancement to support the adaptation. Thus, interoperability of equipment will be a necessity.
- Real-time Reaction—Based upon the capacity for decentralized decisions and guided by IoT such as sensors and actuators, smart components can make corrections in real time.
- Simulation—IoT devices such as sensors and actuators can be emulated so that entire behaviors of smart systems become virtualized.

Other technology trends and principles that are key to Industry 4.0 include big data, cloud, additive manufacturing, AR, robotics, and machine–machine–human integration (Crnjac et al. 2017). The IoT technology is foundational for these mechanisms. IoT provides big data, may include additive manufacturing and robotic instrumentation, and can inform both machines and humans in the loop. A digital twin of an Industry 4.0 plant is the composition of these mechanisms for modeling, monitoring, simulating, and securing the physical plant relative to its environment. One successful digital twin implementation will not simply be copied by other organizations. However, a maturity model can help guide the capabilities and improvements of a digital twin along a path to implement these mechanisms.

There are many different maturity models. Some of the models are well known and not specific to digital twins, such as the CMMi model. Other models have a higher correlation to digital twins based upon their focus on digitalization, such as the SMSRA and M2DDM. Further models have been created by technology and consulting companies that offer solutions or expertise. Those models include examples such as Rockwell Automation, Price Waterhouse Coopers, and Siemens. Data is a core component of many models, including the Maturity Model for Data-Driven Manufacturing (M2DDM). These models and others are listed in Table 2.

A good maturity model removes confusion by isolating the factors and priorities that will help an organization achieve the next level of capability. Parente and Federo suggest removing conjunction, equifinality, and asymmetry for causality in models to be clear to organizations (Parente and Federo 2019). Asymmetry is a characteristic of causality that may explain one result and then fails to explain another result. Asymmetry can create doubt in the accuracy of a model. Equifinality implies that similar benefits and capabilities may be the outcome of more than one level of maturity. When equifinality exists in models, organizations will cease to increase the risk or cost in implementation as the value may not increase. A conjunction is a relationship between technologies, processes, or culture that holds back value creation until all related tenets increase in maturity together. If such related conditions are spread across maturity levels, intermediary benefits offered at lower levels would not become actual value until much higher levels of maturity are achieved. Maturity models should not suffer conjunction, equifinality, or asymmetry.

The ERP 4.0 maturity model by Basl and Novakova (2019) has six levels across dimensions of business model, technology, data, and processes. To construct the model, Basl et al. analyzed trends from survey data and layered the trends into the maturity model levels based upon their frequency found from the survey. The survey was completed by 26 ERP system suppliers (Novakova 2019). Trends having the most frequency of being acknowledged by the system suppliers were positioned higher into the levels of the maturity model. The trends were identified through the survey included cloud, IoT, blockchain, digital twins, edge computing, AI, big data, social networks, and AR/VR. These trends are very similar to those identified through social media analytics and are illustrated as green network nodes in Fig. 9. The most frequent trends include cloud, IoT, and AR. Trends with lesser frequency include extending asset life, optimizing performance, and implementing blockchain. Other trends included big data, mobile ERP apps, and in-memory computing (IMC). A segment of Basl et al. ERP 4.0 maturity model is illustrated in Table 3.

The digital twin maturity model has been informed according to the guidance by de Jesus and Lima of using context, characteristics, expertise, survey (social media analysis), and qualitative research. Academic research, commercial solution and providers' models, and social media analytics were input factors for the creation of the digital twin maturity model. Basl's method utilized in the ERP 4.0 maturity model creation uses trend popularity to determine the maturity levels. While not the final version of our model, the approach by Basl does offer insight into public opinion and the volume of driving trends (as illustrated in Fig. 10).

Table 2 Example maturity models and descriptions

Example models	Short description
Maturity model for data-driven manufacturing (M2DDM)	The Maturity Model for Data-Driven Manufacturing (M2DDM) contains six levels of maturity (begins at level 0). The 4th level is *digital twin* and characterized by smart systems, decentralized decisions, and centralized intelligence to keep humans in the loop. The 5th, and highest level, is the self-optimizing factory (Weber et al. 2017)
Smart manufacturing systems readiness assessment (SMSRA)	The Smart Manufacturing Systems Readiness Assessment (SMSRA) provides manufacturing organizations with an indication of their current factory state compared against a reference model of capabilities. The last stage is *transformed* implying the business has executed a change to its business model (Jung et al. 2016)
Complexity management maturity	The first level of the Complexity Management Maturity is initial and represents that an organization has not yet quantified the amount of complexity at hand
C3M	The C3M model presents five levels of maturity for IT-based case management systems (CSM) across three phases of CSM adoption; pre-CSM, CSM, post-CSM. C3M is novel as it presents levels of capabilities and the risks that may be associated with the levels of benefits (Koehler et al. 2012)
Capability maturity model integration (CMMI)	Capability Maturity Model (CMM) was constructed in 1986 and updated in 2006 to include tech and process as the CMMI model. CMMI includes the phases of initial, repeatable, defined, managed, and optimizing
Test Maturity Model Integration (TMMi)	TMMi utilizes the same structure as CMMi and helps organization gauge and improve their software testing practices (TMMi Foundation 2020)
Industry 4.0/digital operations self-assessment	PWC's self-assessment places an organization's Industry 4.0 capability concerning their target state and offers them a benchmark to the positions of industry competition. Cognet et al. compared the PwC and IMPULS models and found that the IMPULS model has 84% coverage of the PwC digital maturity model's KPIs
The connected enterprise maturity model	Created by Rockwell Automation, this five-stage maturity model offers best practices for modernizing culture and technologies when networking operational technology (OT) and information technology (Parkinson 2015)

(continued)

Table 2 (continued)

Example models	Short description
Digitization roadmap	The digitization roadmap by Siemens is constructed to help organizations transform their business. Six areas, such as process, security, and collaboration, are reviewed and benchmarked and an associated ROI study is completed to evaluate financial consequences of improvement activities (Siemens 2020)

Table 3 A subset of Basl's ERP 4.0 maturity model

Level	Description and inclusion
0	Traditional RDBMS system, with basic ERP process automation, and no cloud adoption
1	Mobility, additional automation, and digitization of processes
2	The complexity, digital capabilities, and analysis all increasing
3	Initial migration to cloud services, business intelligence efforts underway, continued increase in process automation
4	As-a-service implementations, IoT integration, digital twin capabilities
5	AI, RPA, all cloud deployment, all business processes automated

Trends identified from the Industry 4.0 models and academic research, such as decentralized and interoperability, have little mention within our collection of tweets. Collaboration has many more references compared to the two least mentioned topics. Another jump exists between the trends of changeability and predictability; however, the topics of fidelity and autonomy retain the most conversation found in the collection of tweets.

The digital twin maturity model has been constructed based upon the characteristics found in literature review, social media analytics, and based upon input from existing maturity models. The digital twin maturity model is composed of six levels: initial, managed, integrated, immersive, autonomous, and ubiquitous (illustrated in Fig. 11).

The lowest maturity level is the initial digital twin. The initial digital twin is limited in scope, such as only instrumenting a few parts and components. The initial digital twin offers limited insight and is far from being complete, integrated, or even secured. The second level of maturity is the managed level. At the managed level, the twin has a prioritized roadmap and coverage beyond ad hoc parts and includes parity with system components. The third level of maturity increases the digital twin's capability via integration and interoperability. At this third level of integration, the digital twin can model, monitor, and predict many of the physical subsystems. The fourth level of maturity, immersive, is mostly defined by its human interface. At the fourth level of maturity, the digital twin is assessable using immersive interfaces, such as augmented or virtual reality. The autonomous level of the digital twin has

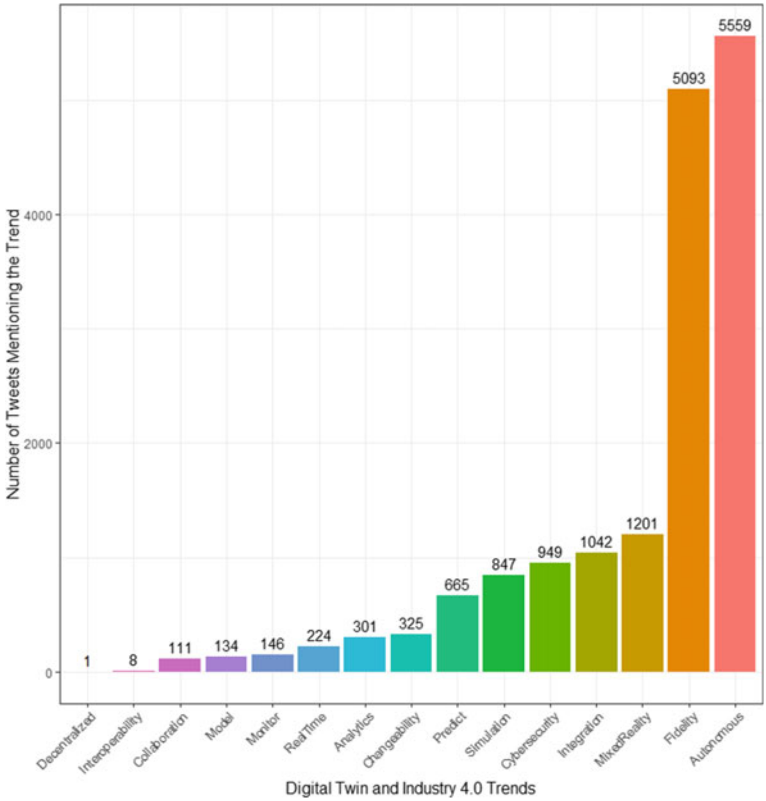

Fig. 10 Amount of maturity level/trend mention in our social media analysis

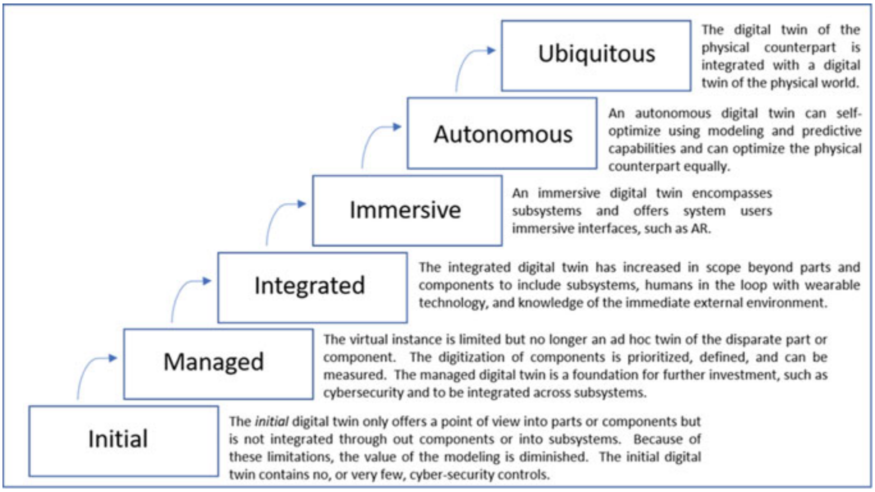

Fig. 11 The six levels of the digital twin maturity model

the cybersecurity, integration, and authority, among other characteristics, to self-optimize its physical counterpart. Finally, the sixth level of maturity of a digital twin is when it consumes the context of its environment. This is the ubiquitous level. This level requires investment and technology that will be beyond the scope of most organizations. Achieving the ubiquitous level requires instrumenting the physical world, beyond the immediate assets, to understand global weather patterns, political, social, and economic phenomena, as well as other growing concerns. Table 4 provides the capabilities and their descriptions.

Referring to Parente and Federo's guidance for models to be effective for organizations, we test our digital twin maturity model for conjunction, equifinality, and asymmetry. Conjunction in a maturity model exists when the benefit promised by achieving a lower level, such as the integrated digital twin, cannot be reaped until the digital twin reaches an advanced level, such as immersive. In our model, for example, value is delivered to an organization at the integrated digital twin level, as that level of maturity allows the twin to grow from modeling individual parts or components into modeling entire subsystems. Furthermore, value is achieved at the integrated level through engaging with users with wearable technology, such as understanding the physical location of system operators for safety reasons. It is clear then that value arrives at the integrated level without requiring the immersive level to have been met.

Table 4 The six levels of capability and a short description of their enablement

Capability	Description of enablement
Initial	At this level of maturity, the digital twin can model a selection of parts or a few components of the system. The digital twin can inform human operators and offers a viewpoint toward collaboration. It is far from a smart or autonomous capability
Managed	Digital twins increase the cybersecurity risk footprint by increasing integration touchpoints and consuming data in transit, storage, and processing. A managed digital twin is measured for its ability to secure itself and the physical asset. The managed digital twin has moved beyond ad hoc instrumentation of parts into a prioritized roadmap that incorporates cybersecurity concerns
Integrated	A complex system is composed of many systems and subsystems. At this level, the digital twin incorporates all targeted data sources into a unified virtual instance of the physical counterpart
Immersive	A digital twin at this level offers a modern and immersive interface with AR or VR capabilities. Beyond monitoring the components, the immersive interface may offer simulated experiences of the components
Autonomous	Once the digital twin is integrated, informed, and secured, it may become *smart* or optimize without decisions from a human control interface
Ubiquitous	Complex systems operate within the context of their environment. A ubiquitous digital twin of a physical asset would integrate with a digital twin of the physical world, such as climate models. This level of maturity requires investment and integrations that organizations will scope out of their implementation for years to come

Similarly, asymmetry would damage the trust in the digital twin model when a characteristic fails to explain its importance in each of its succeeded levels. For example, the integrated digital provides an API that can be consumed by a headset offering an immersive experience. The integrated digital twin also provides interfaces to the sensors and actuators that will be utilized to digitally annotate the physical world through augmented reality. Furthermore, an integrated digital twin is required for the autonomous digital twin to exist. The autonomous digital twin requires integrations to the many parts, components, and subsystems to control and optimize the physical asset. Even the autonomous digital twin requires integration to the digital twin of the physical world. If we moved a step down in maturity, down from the integrated digital twin to the managed, all the previous features and benefits would exist in a product roadmap but not in the implementation. The managed digital twin is more than a simple roadmap and vision, it offers an implementation whose limited existence is now counted (managed and measured) so that vulnerabilities, risk, and remediation are a part of the planning and implementation. Without applying cybersecurity early into the maturity model, future benefits would have a greater risk. Any future maturity state beyond the initial digital twin will always offer the original benefit of the digital point of view into a limited part or component.

The last area to defend the digital twin maturity model includes the characteristic of equifinality. Equifinality implies that similar benefits and capabilities may be the outcome of more than one level of maturity. If a digital twin were at the maturity level of initial, we would not want to allow the twin to become autonomous nor would the benefits of an autonomous system be reached at the initial level. The small scoped system could likely ruin many integrated parts and components, as it is not yet informed of the entire system's states, such as whether dependencies are operating, within appropriate thresholds, failed, or shutdown. The initial twin would need to reach the integrated phase to have this knowledge and should not have widespread integrations with other systems without first safely being counted, measured, and secured in the managed level. The benefit at each phase of our model can be reached at that level, without delaying the benefit until future phases. It is important to note that while cybersecurity is a component of the managed level, cybersecurity must be addressed throughout later phases.

5 Conclusion and Future Work

This chapter introduced findings from social media analytics on digital twins as well as a new maturity model. From the social media analytics, the top three trends identified included the IoT, AI, and industrial uses. An analysis into the industrial uses found the health industry as the most mentioned, followed by entertainment and utilities. The textile industry was not mentioned within the collection of tweets used in this research.

Sentiment analysis was performed on the messages within the tweets and a comparative analysis was offered across industries. Given a tweet references the food industry, there is an 8.0% probability that the sentiment of the tweet will be anger. The probability of the sentiment of trust occurring is highest for the industry of automotive; however, automotive referencing tweets only convey trust with a probability of 40.0%. The sentiment of disgust is rarely found in the tweet messages, the highest probability of disgust was found in messages labeled toward the industry of forestry (1.4%). Given a tweet has the sentiment of anticipation, there is a greater probability that the tweet references the health industry (31.0%) compared to the entertainment industry (8.7%).

Network graphs were utilized to visually identify relationships. Within the analyzed conversations, not all industry-related tweets referenced the top trends. Tweets that reference the food or hotel industries had very little relationship to top trends.

The collection of tweets identifies a peak in the discussions during January 2020. The tweet having the most retweets was retweeted eighty times. That popular tweet's message was like many of the academic definitions reviewed in this chapter, as a virtual model that can bridge the physical and digital worlds.

To help organizations determine the level of value, to further improve, and to enhance their development process, we suggest a digital twin maturity model. The digital twin maturity model is composed of six levels: initial, managed, integrated, immersive, autonomous, and ubiquitous. The maturity model was discussed in terms of conjunction, equifinality, and asymmetry. These three characteristics should not exist in maturity models as they reduce trust in the accuracy and the value that maturity models offer. Future research should focus on case studies, implementing the maturity model, and further evaluating it for accurate causality of benefits achieved in the various phases.

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