

A Survey on Event Prediction Methods from a Systems Perspective: Bringing Together Disparate Research Areas

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Event prediction is the ability of anticipating future events, i.e., future real-world occurrences, and aims to support the user in deciding on actions that change future events towards a desired state. An event prediction method learns the relation between features of past events and future events. It is applied to newly observed events to predict corresponding future events that are evaluated with respect to the user's desired future state. If the predicted future events do not comply with this state, actions are taken towards achieving desirable future states. Evidently, event prediction is valuable in many application domains such as business and natural disasters. The diversity of application domains results in a diverse range of methods that are scattered across various research areas which, in turn, use different terminology for event prediction methods. Consequently, sharing methods and knowledge for developing future event prediction methods is restricted. To facilitate knowledge sharing on account of a comprehensive classification, integration, and assessment of event prediction methods, we combine taxonomies and take a systems perspective to integrate event prediction methods into a single system, elicit requirements and assess existing work with respect to the requirements. Based on the assessment, we identify open challenges and discuss future research directions.

CCS Concepts: • **Information systems** → **Data mining**; **Decision support systems**; • **Computing methodologies** → **Machine learning**.

Additional Key Words and Phrases: Event prediction, artificial intelligence, predictive process monitoring, anomaly prediction, systems engineering

ACM Reference Format:

Janik-Vasily Benzin and Stefanie Rinderle-Ma. 2023. A Survey on Event Prediction Methods from a Systems Perspective: Bringing Together Disparate Research Areas. *ACM Comput. Surv.* 1, 1 (February 2023), 43 pages. <https://doi.org/XXXXXXX.XXXXXXX>

1 INTRODUCTION

Given the rapid growth of data [140] and major advances in enabling technologies such as cloud computing [249], Internet of Things [265], data processing and machine learning [94], it is no surprise that event prediction is researched to a great extent. Event prediction is the ability of anticipating events, i.e., future real-world occurrences. To anticipate events, event prediction processes past events together with further relevant data for learning an event prediction method to map the processed input to predicted future events that are of interest to the respective application domain. Being

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Manuscript submitted to ACM

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able to anticipate events is highly beneficial to many application domains such as business, healthcare, transportation, crime and natural disasters [337]. The value of knowing and ideally understanding predicted future events today lies in the ability of a user in the application domain to act on the predicted future events, e.g., by focusing police resources in areas with high crime risk. To achieve the value, challenges regarding event prediction such as knowledge on the true relationships between causes and effects of events [337], heterogeneous multi-output predictions, e.g., predicting the time and location of future events [248], complex dependencies among the predicted future events as they may interact with each other [198], real-time stream of past events that requires continuous monitoring [256, 267], and challenges in the past event data regarding data properties and quality [256] have to be solved [337].

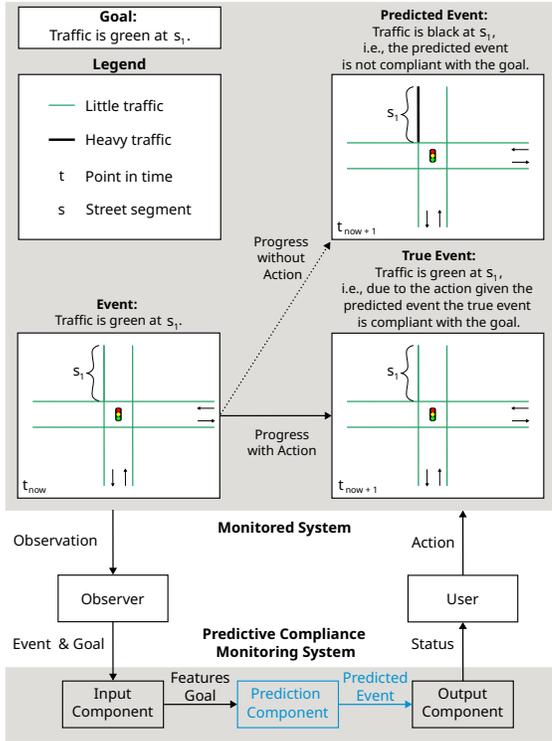


Table 1. List of Abbreviations

Abbreviation	Meaning
PPM	Predictive process monitoring
PCM	Predictive compliance monitoring
CM	Compliance monitoring

Table 2. Application domains of covered articles

Domain	Short	Share	Count
Business	B	0.42	109
Engineering Systems	E	0.12	31
Healthcare	H	0.09	23
Political Events	P	0.09	23
Cyber Systems	I	0.08	22
Media	M	0.07	19
Crime	C	0.06	15
Natural Disasters	N	0.04	10
Transportation	T	0.03	8
Σ		1.00	260

Fig. 1. Event Prediction as a Component of a Predictive Compliance Monitoring System.

Existing work on event prediction has proposed a multitude of different solutions to those challenges. However, the solutions are often only developed within the respective application domain and corresponding research area. Because the type of event and the laws and rules governing the occurrence of events greatly differ among the application domains, e.g., large-scale weather events governed by the laws and rules of meteorology in the domain of natural disasters or small-scale business events of a business process governed by the respective business regulations and internal procedures in the domain of business [9], event prediction research typically approaches the problem in an event-type-and domain-dependent manner [256, 337]. Despite apparent advantages of this approach to event prediction, the result complicates exchanging event prediction methods and solutions for the event prediction challenges with

respect to different application domains and corresponding research areas. Different terminology for event prediction such as predictive process monitoring (PPM) (cf. Table 1) in the field of business process management [72, 211, 290] or anomaly prediction in the field of engineering systems [180] exacerbates the problem of cumbersome method and knowledge exchange among various event prediction research areas. By taking a systems perspective on event prediction leading to a system for event prediction and placing the diverse range of event prediction methods in that system allows to integrate and, thus, foster knowledge and method exchange. Moreover, the system perspective enables the elicitation of general requirements for event prediction methods that serve as a scheme for assessing existing work. A comprehensive assessment of existing work sheds light on potential blind spots missed so far and establishes a well-founded understanding of the current research status for open challenges and future research directions.

To better understand event prediction through a systems perspective, Figure 1 depicts an intersection example from the transportation domain. The intersection has a road segment s_1 that is depicted at two points in time, the current point in time t_{now} and a future point in time $t_{\text{now}+1}$. Our goal for the intersection with road segment s_1 , the *monitored system* in this example, is to maintain green traffic for s_1 , i.e., on road segment s_1 little traffic should be maintained. Currently, event “Traffic is green at s_1 ” at t_{now} *complies with* our goal. This event together with the goal is observed by the *observer*, e.g., a video camera directed at road segment s_1 and a user interface for setting goals. In general, the observer is an abstract interface between the monitored system in the real-world and the system for event prediction, i.e., it typically consists of a set of sensors, user interfaces and/or application programming interfaces.

Then, the observer sends an event and goal to the *input component* of the generalized *predictive compliance monitoring* (PCM) system (cf. Figure 1) to process the event and goal for subsequent prediction by the *prediction component*. *Predictive compliance monitoring* is concerned with continuously anticipating whether the monitored system complies to a goal or set of goals in the future and supporting the user in understanding and acting on the anticipated compliance status [256]. Thus, a generalized PCM system conceptualizes event prediction through its input component and prediction component, i.e., the event prediction method is conceptualized as the prediction component. After pre-processing and encoding the event in the input component, the prediction component predicts “Traffic is black at s_1 ” at point in time $t_{\text{now}+1}$. Hence, the future progress of the monitored system is predicted to be non-compliant with our goal.

The *output component* of the generalized PCM system prepares a status for the user, e.g., an urban traffic control center, that decides on the necessary action to change the future towards a compliant status, e.g., rerouting incoming traffic for road segment s_1 . Due to the action, the ground-true real event (true event) at $t_{\text{now}+1}$ is “Traffic is green at s_1 ” and, thus, compliant with the goal instead of the predicted “Traffic is black at s_1 ” that is non-compliant. To sum up, the user of the application domain is able to anticipate the future of the monitored system with respect to the goal and act accordingly on the account of the generalized PCM system.

The example indicates how the system perspective benefits the integration of event prediction methods by giving the method a general, yet practical context that covers important parts such as goals and actions. To comprehensively classify, integrate, and assess existing work on event prediction methods with the aim of facilitating knowledge sharing and deriving open challenges and research directions, this survey is guided by the following research questions:

RQ1 How can existing event prediction methods be classified?

RQ2 How can existing event prediction methods be assessed in a general, consistent, and systematic manner?

RQ3 To what extent do existing event prediction methods fulfill assessment criteria?

RQ4 Which open challenges and research directions remain in the field of event prediction?

1.1 Related Surveys

Due to its integration aim, this survey is related to different existing surveys. We structure the related surveys along the three pillars of our research methodology as depicted in Figure 2.

Starting with the event prediction survey pillar, [337] surveys the literature on event prediction with the aim of a systematic taxonomy and summary of existing approaches and application domains as well as standardizing event prediction evaluation for facilitating future development of event prediction. Considering the scope of [337], our survey focuses on the event prediction method instead of event prediction (resulting in 107 of the 216 references as depicted in Figure 2) and extends the scope in the direction of uncovered event prediction method research (67 added articles) and uncovered PPM research (86 added articles). Aside from the scope, [337] focuses on the techniques to solve the identified event prediction research problems, e.g., regression, point process and survival analysis technique for solving the problem of predicting a continuous point in time of future events. Hence, the existing approaches are classified and summarized along inherent properties of the proposed solutions. With respect to classifying existing approaches, our survey extends the classification in [337] by abstracting from the respective technique and integrating taxonomies proposed in other surveys [72, 109, 211, 256]. With respect to summarizing existing approaches, our survey extends the summary in [337] by summarizing existing work along the requirements for event prediction methods that we elicit through a systems perspective, i.e., our summary takes an external, systems perspective on event prediction compared to the internal, methodological perspective of [337]. Furthermore, the requirements are used to assess existing event prediction methods, resulting in a comprehensive assessment that further extends [337].

The event prediction search pillar includes eleven surveys [20, 109, 120, 130, 135, 205, 209, 230, 250, 281, 283]. Each of these surveys has a certain scope, e.g., [205, 209] focus on time-series data, [281, 283] focus on event prediction of business processes, and [20] on unstructured text events. When compared to the survey at hand, on top of a narrow scope, the eleven surveys neither take a system perspective to generally place event prediction method in a context, nor elicit requirements for assessing the methods, nor comprehensively assess existing work. [109] proposes a taxonomy for event prediction methods with a concept of domain-specificity that is integrated in our taxonomy.

The PPM research pillar includes 22 surveys [71, 72, 116, 141, 154, 157, 160, 167, 207, 211, 216, 222, 247, 256, 273, 275, 281, 286, 290, 297, 316, 318]. Similar to the surveys in the remaining event prediction pillar, the scope of the existing 22 surveys is limited. While the scope in the remaining event prediction pillar is heterogeneous, in the PPM pillar it is homogeneous and exclusively focuses on next events (e.g., [281]) or key performance indicators of business processes (e.g., [297]). [256] is the only PPM survey that takes a systems perspective for eliciting requirements and assessing existing PPM methods. The scope in [256] includes compliance monitoring (CM) (cf. Table 1), i.e., the ability to continuously monitor the compliance status of a business process with respect to a set of compliance constraints, to investigate the potential benefits of combining CM and PPM with respect to the established CM functionalities framework [193]. The investigation result is PCM as a combination of PPM and CM from a systems perspective. Existing work on CM and PPM is assessed with respect to an extended CM functionalities framework with a particular focus on prediction. Our survey generalizes the PCM concept to event prediction, develops a conceptual PCM system and extends and integrates the requirements in [193, 256] with the challenges in [337] and requirements contained in the 260 articles of our existing work selection. [72, 211] propose a similar concept of domain-specificity for classifying PPM methods that is generalized and integrated in our taxonomy, while the distinction in [256] into methods that directly predict the goal of PPM and methods that indirectly predict the goal of PPM via an intermediate representation is generalized and integrated in our taxonomy. For instance, the PPM goal is the late shipment status of online shop

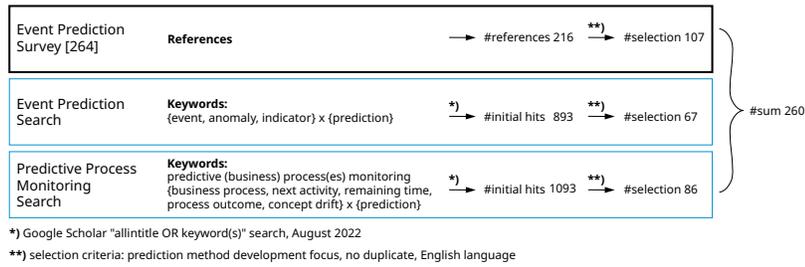


Fig. 2. Methodology for Literature Compilation

delivery packages. Predicting the late shipment status of an online shop delivery package is directly predicting the PPM goal and conceptually similar to the traffic status in the intersection example (cf. Figure 1). Predicting all future events pertaining to the delivery package and, then, evaluating the shipment status on the future events is indirectly predicting the PPM goal and conceptually similar to predicting the number of vehicles on road segment s_1 to subsequently derive the traffic status in the intersection example.

All in all, our survey integrates various scopes of existing surveys and takes a system perspective for placing event prediction in a general context, eliciting requirements and assessing existing event prediction methods.

1.2 Research methodology

We follow a twofold methodology for selecting relevant articles in the event prediction literature. First, we take the recent survey in [337] as a baseline on existing work. Second, we extend the baseline by searches in two directions: event prediction to capture uncovered event prediction method research of the baseline and predictive process monitoring as event prediction literature that uses different terminology. The twofold methodology is illustrated by black and blue color respectively in Figure 2 together with keywords for searches and the results.

Then, we apply the same filter denoted by **) in Figure 2 on each stream of literature resulting in selections that represent significant advancements in prediction method development, i.e., work that focuses on novel event prediction methods instead of only applying a classical machine learning algorithm to a new application domain or focusing on domain-specific feature engineering. Lastly, we take the union of the three selections yielding 260 articles covered in this survey. These articles span a wide array of different application domains each having a large enough absolute article count for proper representation (cf. Table 2).

1.3 Contribution and Structure

Taking a systems perspective on event prediction methods to integrate disparate areas of research results in the following four contributions of this survey:

- **Comprehensive classification of event prediction methods from a diverse range of application domains and disparate research areas.** Event prediction method research spans areas like social sciences, medicine, engineering, and computer science. Researchers at the intersection of these areas and data mining / machine learning propose a large collection of existing event prediction methods. This collection is classified using a taxonomy to support practitioners in finding suitable methods and researchers in developing new methods.

- **Integration of disparate research areas through the generalized PCM system and requirements elicitation for event prediction methods.** By taking a systems perspective, we identify an event prediction method as a component of a generalized PCM system. The generalized PCM system further integrates contributions from the various research areas on event prediction methods. The aim of this integration is to elicit similar requirements for event prediction methods and to facilitate the mutual exchange of method features. Method features are properties of the event prediction method that meet the requirements.
- **Qualitative assessment of existing methods with respect to the requirements and thorough analysis of current research status.** A qualitative assessment of all existing methods gives an in-depth view on the current research status. The current research status is illustrated with examples from the literature, analysed with respect to potential dependencies between requirements and discussed in detail.
- **Open challenges and discussion of future research directions.** The assessment result sheds light on blind spots that embody open challenges to be solved by future research. We identify five challenges and discuss the possible future research direction for each challenge.

The remaining survey is structured into five sections of which the first four correspond to the four research questions respectively. To begin with, Section 2 introduces a notion of an event prediction method, a taxonomy and according classification of existing event prediction methods (\mapsto RQ1). Section 3 gives the reasoning for placing an event prediction method as an integral component into the generalized PCM system, presents the generalized PCM system in detail and explains the requirements for assessing event prediction methods (\mapsto RQ2). Then, Section 4 shows to what extent existing prediction methods fulfill requirements and pinpoints exemplary method features that meet the respective requirement (\mapsto RQ3). Next, Section 5 highlights major open challenges and distills research directions (\mapsto RQ4). Lastly, Section 6 concludes and identifies limitations of the survey.

2 A NOTION AND TAXONOMY FOR EVENT PREDICTION METHODS

This section first introduces a notion of the event prediction method (Section 2.1). Then, it presents the rationale for our taxonomy of event prediction methods and the classification of event prediction methods based on our taxonomy (Section 2.2).

2.1 Event Prediction Method Formulation

In the beginning, event prediction requires a goal or a set of goals that is either formulated by researchers during their motivation for advancement of event prediction methods or by practitioners during implementation and application of event prediction. Without the prediction goal, we do not know what we predict and lack a purpose for predicting. Prediction goals are as diverse as event prediction domains are. For example, "The traffic is green at s_1 " for the intersection example depicted in Figure 1 is an event prediction goal or "Reduce re-hospitalization and increase treatment outcome of heart failure patients" [80] is a set of event prediction goals. Event prediction goals define the monitored system implicitly or explicitly and how we perceive various current and future states of the monitored system by differentiating desired or compliant from undesired or non-compliant states. In the case of the intersection example, the goal implicitly defines the monitored system to be the depicted intersection and that green traffic is regarded as compliant, whereas black traffic is regarded as non-compliant. In the case of hospital patients with previously diagnosed heart failures,

the goal defines the monitored system to be hospital heart failure patients and that future states with reduced re-hospitalization counts or rates and improved treatment outcome statistics are desired in contrast to, e.g., states with constant re-hospitalization.

Definition 2.1 (Event Prediction Goal). An event prediction goal g is a well-formed formula in some logic G with atomic propositions over the domain of the monitored system that evaluates to either true or false given some predicted instantiation of its variables. If the event prediction goal g evaluates to true, we say the monitored system future state is compliant, otherwise it is non-compliant.

For the sake of simplicity, we did not state the presented examples as actual formulas of a logic such as propositional logic or linear-time logic and point towards existing methods on translating natural language to formulas, e.g., of linear-time logic [31]. The two important points here are the existence of at least one event prediction goal and that it is stated in terms of atomic propositions over the domain of the monitored system (implicitly or explicitly).

Based on the event prediction goal and the monitored system, we identify two kinds of data used for event prediction¹: Historical event data $Y_0 \subseteq \mathcal{T}^- \times \mathcal{L} \times \mathcal{S}$ and historical indicator data $X \subseteq \mathcal{T}^- \times \mathcal{L} \times \mathcal{F}_I$, where \mathcal{T} is the time domain, $\mathcal{T}^- \equiv \{t | t \leq t_{\text{now}}, t \in \mathcal{T}\}$ are all times up to the current time t_{now} , $\mathcal{T}^+ \equiv \{t | t > t_{\text{now}}, t \in \mathcal{T}\}$ are all times after the current time, \mathcal{L} is the location domain, \mathcal{S} is the event semantic domain and \mathcal{F}_I is the indicator feature domain that does not include the time and location domain [337]. Data types Y_0 and X are generated by the observer (see Figure 1) through observing the real-world, e.g., the observer generates an event $y = ("05.01.2023\ 13:00", "s_1", "Traffic = green")$ by observing that two vehicles have stopped in front of the red light and an indicator $x = ("05.01.2023\ 13:00", "s_1", "Workday = Yes")$. This data is sent alongside the event prediction goal to the input component of the PCM system (cf. Figure 1 and Section 1) that maps the data to suitable features $F \subseteq \mathcal{T}^- \times \mathcal{F}_Y \times \mathcal{F}_X$, where \mathcal{F}_Y is the domain of features based on historical event data and \mathcal{F}_X is the domain of features based on historical indicator data, by means of preprocessing and encoding. The input component outputs the features and prediction goal to the prediction component that is realized by an event prediction method, e.g., $f = ("05.01.2023\ 13:00", (1, 0), 1)$ for a one-hot encoded traffic value and identifying the workday by 1.

Definition 2.2 (Event Prediction Method [337]). Given features $F \subseteq \mathcal{T}^- \times \mathcal{F}_Y \times \mathcal{F}_X$ and an event prediction goal $g \in G$ or set of goals, an event prediction method outputs predicted future events $\hat{Y} \subseteq \mathcal{T}^+ \times \mathcal{L} \times \mathcal{S}$ such that for each future predicted event $\hat{y} = (t, l, s) \in \hat{Y}$ for $t > t_{\text{now}}$ it holds that (C) either the goal g or the set of goals is itself a future predicted event or it can be evaluated on the future predicted events.

In the traffic example, let us assume that we learn a neural network model that takes the most recent feature f and outputs $\hat{y} = ("05.01.2023\ 14:00", "s_1", "Traffic = black")$ as the predicted future event (cf. Figure 1), i.e., the goal is itself the predicted event. Consequently, the future state of the road segment s_1 's traffic is predicted to be non-compliant, so an action by the user is required.

Following our scope and aim (cf. Section 1.1 and Section 1.2), we separate feature engineering from event prediction and focus on the remaining event prediction method. We further add condition (C) on prediction goals such that the event prediction method has an explicit aim expressing our reasons why we are interested in predicting the future events and how we perceive the possible predicted future events, namely as compliant with our desired future state or as non-compliant. Defining event prediction methods with an explicit goal has three benefits. First, all existing work in

¹In the following, we adopt the existing definition of the event prediction problem and method in [337] as close as our different perspective and scope allows.

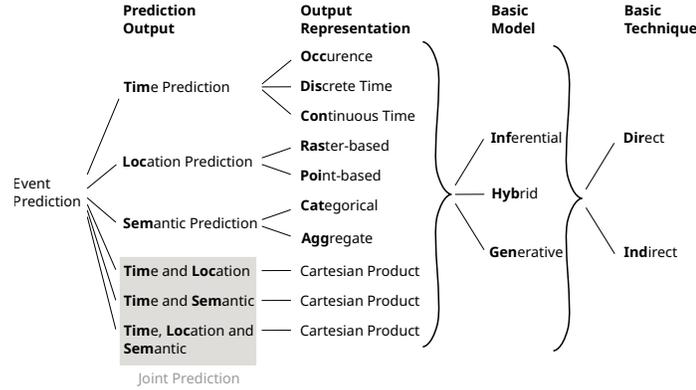


Fig. 3. Taxonomy of event prediction methods [109, 256, 337]. Abbreviations for each class highlighted in bold.

our selection state a goal or set of goals in their motivation that expresses why predicted future events of the method are of interest to the user and how a specific predicted future event is perceived, e.g., [80] predict future patient treatment outcomes in clinics for a proactive treatment effect analysis. Hence, including condition (C) in the definition combines the *how* (i.e., the event prediction method) and the *why* (i.e., the prediction goal) for event prediction. Second, it links predicted future events to actions. Since an action aims to change a monitored system towards a desired state, linking actions to future predicted events requires a notion of a desired state. With prediction goals the notion of desired states is defined by compliant or desired future states and by non-compliant or undesired future states. Based on this notion, an action can aim for a desired future state of the monitored system. Third, condition (C) emphasizes how we can decide whether a specific event prediction method is successful in predicting future events.

Furthermore, the condition (C) captures the fact that not all prediction methods predict occurrence times, locations and semantics of future events simultaneously, as many focus on a single domain that is sufficient for the prediction goal, e.g., [78] focuses on the time domain by predicting the occurrence of abnormal deformations for a single machine tool of a production facility, [237] focuses on the location domain by predicting the area that a particular crime will occur and [200] focus on the semantic domain by predicting the future activity of a business process instance [337].

2.2 Classification of Event Prediction Methods

Event prediction is a challenging and complex endeavour that spans many, diverse research areas and application domains. Plenty of methods can predict future events, yet we can navigate through the large body of existing work in a quick and structured manner by means of a simple taxonomy as depicted in Figure 3. First, we describe and explain the taxonomy in Section 2.2.1 and then present the classification of the 260 selected articles aggregated by the first level of the taxonomy tree in Section 2.2.2.

2.2.1 Taxonomy of Event Prediction Methods. In the following, we present a taxonomy of event prediction methods in Figure 3 that aims at integrating and generalizing existing taxonomies in a consistent and concise manner. The first two levels of the taxonomy, the prediction output and output representation, are based on [337], while the third level, *basic model*, generalizes ideas from [72, 109, 211] and the fourth level, *basic technique*, generalizes [256] and captures the two ways a prediction goal is related to an event prediction method (cf. condition (C) in Definition 2.2).

Prediction output. Event prediction method outputs are heterogeneous due to many different prediction goals that refer to heterogeneous domains such as healthcare, cyber systems or transportation. Nevertheless, four broad classes of prediction outputs are sufficient to represent this heterogeneity: *time* (tim), *location* (loc), *semantic* (sem) and *joint* prediction as depicted in Figure 3. Event prediction methods that focus on the time domain of future events, i.e., when the future event is predicted to occur, are classified into the *time* prediction output, e.g., forecasting the future progress of a machine sensor time-series [13] or predicting the time-to-event for patient treatment outcomes [103]. If the focus of the method is on the location domain of future events, i.e., where the future event is predicted to occur, the method is classified into the *location* prediction output, e.g., predicting the next place of social media users [308]. Event prediction methods classified into the *semantic* prediction output focus on the semantic domain of future events, i.e., what the future event means or how the event, that typically involves symbols or natural language, can be described, e.g., predicting the next activity of a business process [200]. The joint prediction class is the only class that focuses on simultaneously predicting multiple prediction domains of future events such as the time and location domain.

Output representation. Depending on the prediction output type, research has represented the respective output differently, i.e., each prediction output class can be further distinguished by its output representation [337]. The time prediction output has been represented as either a binary classification task that signifies whether the predicted event occurs in the future or not (*occurrence* (occ) in Figure 3), or a discretization of the future time domain into time bins with the output being the specific time bin that the future event is predicted to occur (*discrete time* (dis)) or a straightforward, continuous value in the time domain (*continuous time* (con)). The location prediction output has been represented as a grid cell that is the result of rasterizing a continuous space into spatial regions (e.g., integer-valued longitude latitude coordinates in the geographic coordinate system [48]) yielding a *raster-based* (ras) representation or as a point in the continuous space (*point-based* (ras)). The semantic prediction output has been represented as a categorical variable, e.g., the activity label of a business process event, or as an aggregate variable, e.g., a set of key-value pairs for sentences consisting of a subject, object and verb.

The next two levels of the taxonomy tree focus on the similarities of existing work in their developed event prediction method, i.e., despite the heterogeneity of domains, methods, outputs and output representations, they all share only three types of basic models and two types of basic techniques.

Basic model. The basic model underlying every event prediction method is distinguished into *inferential* (inf), *hybrid* (hyb) and *generative* (gen) [109]. This distinction may be called differently, e.g., *implicit* vs. *explicit* [72] or *process-unaware* vs. *process-aware* [211], yet in every instance identifies the type of model employed for developing the method with varying degree. The differentiating property of the model is the degree of knowledge the modeller has or can theorize about the (prediction) goal-dependent salient factors of the system under research. For example, predicting the patient treatment outcome in clinics results in the goal-dependent salient factors to be known risk factors for a negative treatment outcome.

If the degree is high, in the *generative* model class, the modeller applies specific knowledge of the goal-dependent salient factors, e.g., of the nature and the rules, guiding the monitored system that determine or significantly influence the evolution of events to design more specific, customized models and explicitly leaves out factors that can be shown to be irrelevant for the evolution of events. Thus, the modeller develops a counterfactual explanation of the event evolution in the monitored system expressed through the model [254]. The result is often a computational model that can be executed or simulated [314]. For example, business processes can be modelled by the Business Process Modelling Notation (BPMN) [51] or a similar business process modelling notation that carries the knowledge about business processes such as the observation of decision points for process instances. Comparing this knowledge and type of

model to a weather system, we cannot, for example, ascertain similar decision points in the weather system, i.e., the business process model is specific to properties of the application domain and, thus, only explains next activities of business processes and not what the weather on the next day will be.

If the degree is low, the monitored system is either not researched in detail yet or its nature is too complex in order to pinpoint a fitting class of knowledgeable models for its behavior. Consequently, in the *inferential* model the modeller applies generic, mathematical models [314], e.g., a regression model for predicting the time bins of future anomalies in long term evolution (LTE) mobile networks [115], that learn patterns in the data observed from the monitored system to predict its behavior. Here, the knowledge about goal-dependent salient factors may still enter the overall PCM system, but through domain-specific feature engineering and not through the event prediction method design and its underlying basic model type.

Lastly, in the *hybrid* case the modeller develops an event prediction method whose model can be divided into a part for which the generative approach is applied and a part for which the inferential approach is applied, e.g., learning a Markov chain model (*inferential*) for each state of a BPMN process model of a business process (*generative*) for predicting probabilities of next activities executed for a specific process instance [159].

Basic technique. The basic technique underlying every event prediction method is distinguished into *direct* (dir) and *indirect* (ind). Any event that can be generated through observing the real-world is generated by means of a similar formula as the prediction goal (cf. Definition 2.1). That is, at some point before the prediction, we introduce a formal notion of what constitutes an event given the real-world or the recorded data. This formal notion is expressed through the formula, e.g., green traffic is constituted by up to two vehicles on the monitored road segment before the intersection or a crime is constituted by the respective law that is used to convict the guilty. In the latter case, the evaluation of the law to either true or false may be up to the respective court, but in the data this ambiguity does not usually show up. Overall, an event is defined by a formal notion and the prediction goal is defined by another formal notion.

If the output of the prediction method given the features is the prediction goal itself, the prediction goal is *directly* predicted as a future event (cf. first part of condition (C) in Definition 2.2). This is the case for the example in Section 2.1 in which the neural network predicts orange traffic. If the output of the prediction method is a predicted future event or multiple future events on which we evaluate the prediction goal, then the prediction goal is *indirectly* predicted through future events (cf. second part of condition (C) in Definition 2.2). For example, [13] first predict the evolution of machine properties observed by sensors and then evaluate prediction goals defining certain types of anomalies on the predicted time-series. To put it in other words, the direct technique defines the output of the prediction method as the value of the prediction goal, whereas the indirect technique defines the output of the prediction method as an intermediate notion of an event on which the prediction goal can be evaluated. The choice of basic technique has major consequences on the architecture of the PCM system and its properties, as we will see in Section 3.1.

2.2.2 Classification of Existing Work. Overall, 154 articles belong to the class of time event prediction, while 10 articles, 46 articles and 49 articles belong to the class of location, semantic and joint prediction respectively. Hence, most of the existing work on event prediction focuses solely on the time domain. If we consider the importance of the time domain for prediction, this is no surprise. By focusing on a single or small set of prediction goals and a tractable set of events such as a certain set of machine anomalies for engineering systems, treatment outcomes for hospital patients or crimes in a certain geographical area, research on time prediction breaks the complexity of event prediction down to a bearable level while maintaining its attractiveness.

As a consequence of this active research on time prediction, most of the classes are occupied as depicted in Table 3, i.e., most of the various combinations of output representation, basic model and basic technique have been at least researched once. The largest single class is directly predicting the occurrence of the prediction goal with an inferential model. Here, the majority of work chose the business domain as its application. This finding is a direct consequence of active research on predicate prediction for outcome-oriented PPM with the use of standard machine learning methods, i.e., predicting the process outcome or remaining time of process instances expressed through the prediction goal without predicting further domains such as the next activity in the semantic domain is the most active research field in the BPM community [256].

Interestingly, the indirect technique for generative models is consistently missing in time (cf. Table 3), location (cf. Table 4), semantic (cf. Table 5) and joint prediction (cf. Table 6). Taking these missing classes together with a decreasing number of methods from inferential to generative model type, the research direction on integration of mechanistic knowledge and data-driven models in [337] is illustrated.

Considering the existence of many classes with very few work, 19 classes with only a single work and nine applications domains, a large area of possible research remains open despite active and already considerable research on event prediction. In Section 5, we will deepen our insights on possible areas for further research and discuss how this relates to commonly interesting prediction goals in the various application domains. For now, taking the classification results as a starting point, researchers can quickly search for conceptually related work in other application domains that often also implies a different research area and community, while practitioners can use this classification to look for suitable work on their respective problem.

3 COMPREHENSION OF EVENT PREDICTION METHODS THROUGH THE GENERALIZED PCM SYSTEM

If we want to fully understand event prediction in all of its heterogeneous aspects, multi-scale dimensions and overall complexity, we must achieve to grasp the set of systematic relationships of the system in which event prediction is conceptualized or implemented [84, 85, 110, 155, 254]. This feature of understanding emphasizes the need for a systems perspective on this topic. In general, considering the diverse nature of prediction goals throughout the various application domains, the type of system for event prediction must be a decision support system rather than an autonomous system, i.e., the user that decides what action is carried out is a human person (cf. Figure 1 and Figure 4). For instance, deciding on the treatment plan of patients based on predicted future treatment outcomes must be done by physicians [65]. Furthermore, the utility of event prediction critically depends on the lead time, the time from the prediction of an event to the true event time. This property necessitates a prediction at run-time and, thus, an online, stream-based conceptualization of the event prediction system [267]. The source streams have to be continuously monitored such that the lead time is as large as possible [337]. Altogether, we need a decision support system that continuously monitors and predicts with the aim of distinguishing non-compliant, action-demanding from compliant future states.

To that end, we present a conceptual PCM architecture that entails these properties in Section 3.1 and elicit assessment requirements in the form of requirements from the system architecture in Section 3.2.

3.1 Widening the Scope: Event Prediction Method in the PCM system

Before we can present the PCM system in detail, we elaborate on how it applies to event prediction. Through our elaboration, we understand how multiple research areas work towards the same goal with more or less similar methods,

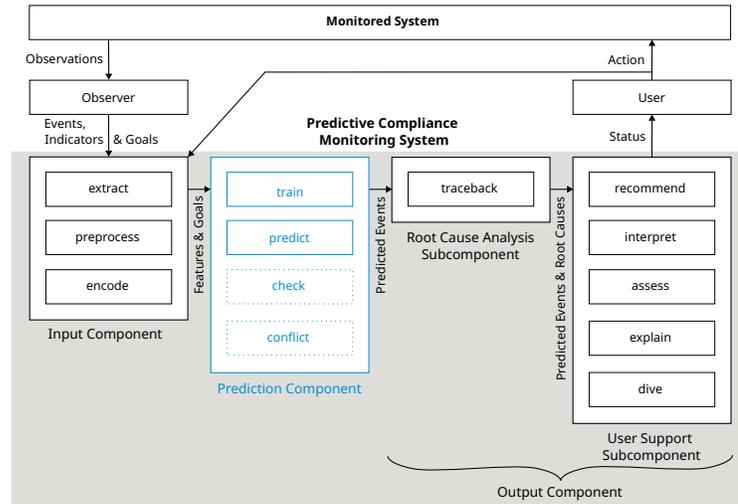


Fig. 4. Generalized Predictive Compliance Monitoring System - Conceptual and Structural View

yet different terminology. Moreover, we illustrate the community- and application-domain-spanning characteristic of event prediction.

In the field of business process management, a PCM system aims to help companies monitor and understand the future compliance status of their business processes to act proactively towards a desired future compliance status [193, 256]. To that end, a PCM system integrates research on CM and PPM. CM aims to evaluate compliance constraints on the current and future events or key performance indicators of a business process [193], while PPM aims to predict the future events or key performance indicators of a business process [72, 211]. By comparing CM, PPM, and the event prediction method definition (cf. Definition 2.2), we identify the following similarities: compliance constraints are prediction goals, future key performance indicators of a business process correspond to future predicted events (cf. condition (C) in Definition 2.2), PPM is an event prediction method, and the business process is a monitored system.

All in all, if we generalize

- (1) the monitored business process and its events as a monitored system and its events,
- (2) the prediction of the future compliance status as event prediction methods,
- (3) the anticipated compliance status as the evaluation result of an event prediction goal,
- (4) and the proactive actions as any action an user can take with the support of a decision support system,

then the generalized PCM system depicted in Figure 4 is a conceptual model of decision support systems featuring event prediction. Not only does this generalization place event prediction inside a generic system necessary for understanding its merits more deeply, it also represents an integration of research on the various aspects of event prediction and monitoring into a common theme. Furthermore, the generalization of a PCM system from business process management to a decision support system for event prediction in general enables us to mutually transfer requirements and solutions between the respective research areas.

A PCM system consists the input, prediction, and output component (cf. Figure 1) which are refined in Figure 4. Moreover, a feedback cycle is added from the user to the input component that contains the action as a more direct and efficient way of accounting for the effects of decided upon actions onto the monitored system in the PCM system [337].

Input component. The input component *extracts* data from the observer, *preprocesses* the data and *encodes* it into the respective feature space required by the event prediction method (cf. Definition 2.2). In practice, the input component has to implement the various functionalities of *data collection* proposed by the data management community, in particular data acquisition and data labeling [260]. Within data acquisition, the tasks of augmentation through data integration / data fusion are particularly important, while for the case of input event data lacking an event notion, the task of data programming or event extraction [75] become additionally relevant. Considering that the observer is only an abstraction for multiple, heterogeneous data sources, the input component's *extract* functionality has to deal with challenges of raw data ingestions from various data sources [199].

The input component's *preprocess* functionality covers the transformation of ingested data to a common representation based on a series of rules [139], data cleaning [132], schema matching for relational data [246], deduplication and record linkage [86, 107, 214], and, finally, canonical column selection for relational data [276]. In the case of non-relational data such as continuous, unlabelled sensor readings, schema matching is replaced by data programming or event extraction [75] to define an event notion for event sources. In case of low-level events coming from the event source, the task of event abstraction [294] may be necessary. Since events from multiple sources may actually be the same event, these events have to be matched to finalize the data integration. As a last step in the input component, the *encode* functionality maps the integrated data to the event and indicator feature space. Here, it is important to follow the principles of feature engineering [345], while the resulting features are typically application domain- and/or prediction goal-specific.

Prediction component. The prediction component is realized by an event prediction method that *trains* a prediction model and *predicts* the future events. In Definition 2.2, the future event can either be (i) the prediction goal or (ii) an intermediate event on which the prediction goal can be evaluated. Case (i) does not require the additional functionalities *check* and *conflict*. For case (ii), the evaluation of the prediction goal is realized by *checking* the compliance of the intermediate event with respect to the prediction goal. If a monitored system is subject to a set of prediction goals, these goals may be in conflict [193]. The PCM takes this possibility into account when checking the set of prediction goals on the intermediate event and includes this information in its output.

Output component. The output component is refined into two subcomponents; The **root cause analysis component** and the **user support component** to underline the need for model transparency and interpretability (in short explainability), accountability, and prescriptiveness [193, 256, 337]. The ability of the PCM to *trace* the non-compliance of the future events *back* to the root cause(s) contributes to an explainable and actionable prediction. The prediction with root cause analysis is explainable, because a causal relationship between a root cause and its anticipated result exists [254]. Furthermore, root cause analysis makes the prediction actionable, since the user can derive countermeasures for non-compliant future events through acting on the root causes. Researchers in the application domains of engineering and cyber systems, i.e., IT systems, typically develop root cause analysis for explaining the root causes of machine faults or system anomalies to the operation manager [83, 195].

Finally, the PCM system supports the user in understanding the results and acting on them. To that end, the user support subcomponent *recommends* actions and countermeasures for non-compliant predicted future events [229], *interprets* the impact of the proposed actions on the predicted future events [111], and *assesses* the overall uncertainty that remains throughout all prior functionalities [131]. Separately showing all the results to users may quickly overwhelm, distract from major points, and hinder understanding, which is why the gist of the results are *explained* to them. In

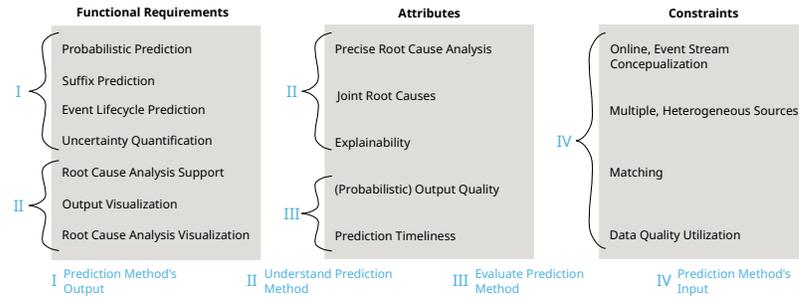


Fig. 5. Requirements engineering result for event prediction methods in the context of predictive compliance monitoring systems categorized by functional requirements, attributes and constraints [108] and annotated by the requirements respective target.

Section 5, we discuss a potential approach to this challenging functionality. If the gist is first explained to the user, but more detailed information is necessary for understanding or analysing, the user can *dive* into the respective results.

All in all, principles of systems engineering applied to the design of a conceptual decision support system featuring event prediction result in a new perspective on event prediction [24]. This new systems perspective encompasses a holistic view on the many facets of event prediction, yet is simple enough to guide us in our understanding of functionalities surrounding the actual prediction that are necessary to hone its value.

3.2 Assessment Scheme for Event Prediction Methods

After our refined understanding of event prediction through its conceptualization as a component of PCM systems, we take the systems perspective one step further by eliciting requirements for event prediction methods from existing surveys [193, 256, 337] and iteratively refining them during the assessment of the 260 articles in our selection. Aside from advancing our account of event prediction, the requirements serve as an assessment scheme for assessing the selection of existing work.

Following a concern-based taxonomy of requirements [108], the 16 event prediction method requirements in Figure 5 are classified into seven functional and nine non-functional requirements in the form of five attributes and four constraints. Attributes specify qualities of the method, whereas constraints limit the solution space from which methods can be instantiated. Furthermore, each requirement is assigned to one of four specification targets: (I) the prediction method's output, i.e., the properties of predicted future events, (II) understanding the prediction method, i.e., properties or qualities of the method that help to grasp the systematic relationships between the prediction and its input through, for example, visualization [8, 208], (III) evaluating the prediction method, i.e., what qualities are presented for evaluation, and (IV) the prediction method's input, i.e., what properties of the input were considered in developing the method.

Functional requirements. Considering that the real-world is complex, chaotic, and imperfect, a deterministic prediction of future events idealizes and keeps important nuances in the future events from the user [254, 256, 337]. Therefore, a *probabilistic prediction* that includes information on the likelihood of the predicted future events actually occurring is required. If we want to enable the user to optimize decisions with respect to a comprehensive anticipation of the future, predicting the next event is not enough. A *suffix prediction* specifies the need for anticipating more events following the next event, e.g., knowing of the next three heavy rainfalls instead of the next one, officials can more efficiently allocate resources. Instead of increasing the anticipated time horizon as suffix prediction does, *event lifecycle prediction* refines the granularity of the anticipated event time horizon. Although events are typically conceptualized as

real-world occurrences happening at a certain point of time, each real-world event has a duration and, thus, at least a *start* and an *end* point of time [165, 193]. If we do not predict the lifecycle of events, we are, for example, not aware of the time period affected by the event. Our travel plans remain unchanged, if the traffic jam is likely to vanish by the time we arrive at its location.

As the last functional requirement specifying the method’s output (I), *uncertainty quantification* aims at reflecting the epistemic and aleatoric uncertainty of the method’s output [131]. Epistemic uncertainty consists of model and approximation uncertainty and is the result of our lack of knowledge on the true relationships of the monitored system necessary for the design of a perfect prediction method. As such, it is reducible by further research. Aleatoric uncertainty is an irreducible uncertainty that captures the non-deterministic nature of real-world occurrences. Recently, method development acknowledged the existence of both types of uncertainty and incorporated their quantification in its output [317]. Uncertainty quantification can build trust for the prediction method by measuring confidence metrics [337] that accompany probabilistic outputs and improves the subsequent actions, as the user can decide to wait for more certain prediction results that are more likely to occur.

Despite the fact that root cause analysis and visualization are separated from prediction in the PCM system (cf. Figure 4), it is important that the method itself enables these functionalities or already presents a proof of concept on how these functionalities can be done. Otherwise, it will be more difficult for researchers and practitioners to develop these functionalities given only the method itself. Thus, *root cause analysis support* (RCA support), *output visualization* and *root cause analysis visualization* (RCA visualization) indicate whether the proposed method clearly defines how to achieve root cause analysis or visualization on top of the method respectively or already presents a proof of concept.

Attributes. The first set of attributes are the specific qualities *precise root cause analysis* (precise RCA), *joint root causes* (joint RCs) and *explainability* that are essential for an event prediction method, since this first set of attributes helps the user to quickly grasp the situation and act accordingly. The method should enable the precise identification of root causes and detect that multiple true root causes for different predicted future events may, in fact, be the same true root cause. As it is out of the scope of this survey to assess the full variety of how explainability can be achieved or conceptualized [16, 34] and there is no widely accepted definition [34, 104, 254], we limit the attribute to a distinction between *black box* models that are intransparent, *white box* models that are transparent, and a combination of both [34]. Taken together, these three qualities determine the accountability of the method to a large extent. If the user can explain the predicted future events as prerequisites to an optimal strategy for acting on the true root causes, the method and the user both should not be held accountable in case something goes wrong.

The second set of attributes are performance attributes that evaluate the event prediction method itself. [337] presents how the output quality of an event prediction method is evaluated. Considering the requirement on a *probabilistic output quality* (probabilistic quality), we further require a probabilistic evaluation, e.g., with the Brier score [18] or some other appropriate scoring rule [41]. *Prediction timeliness* pertains to the speed a method is able to predict. It determines the lead time, but as a result of concept drift, the training time also has an effect on the lead time. Concept drift due to changing environments such as the COVID-19 pandemic lead to outdated historic data [228, 258, 337]. Consequently, the prediction model must be kept up-to-date. Having to update prediction models results in the training time of the method playing an additional role for a timely prediction, yet we do not know the significance of this role. Moreover, it is not clear what the optimal time for updating is. Aside from these unknowns, training and prediction time comparisons are only reasonable in a fair benchmark that goes beyond the scope of this survey. Hence, prediction timeliness is not assessed in Section 4.

Constraints. The event prediction method is constrained by four properties of the input. First, *online, event stream conceptualization* (online conceptualization) is a consequence of the need for monitoring and timely prediction [256, 337]. A method may fail to show how it can be applied to an event stream at run-time. Since there is a difference between online prediction based on an event stream and offline prediction based on an ex-post dataset, e.g., in terms of efficiently storing and updating already received events from the event stream [54], offline event prediction methods may be unsuitable for monitoring.

Second, *multiple, heterogeneous sources* (multiple sources) limit the method solution space to methods that are aware of or actively deal with the challenges of data integration (cf. input component in Section 3.1). Although overcoming these challenges is the responsibility of the input component in a PCM system, the solution may affect the event prediction method, e.g., by necessitating multiple prediction models [248].

Third, the challenge of *matching* events from multiple data sources is emphasized as a separate constraint (cf. input component in Section 3.1). The matching strategy for the input should be consistent with the strategy for matching events in prediction goals to predicted future events and the strategy for matching events for evaluation purposes. Multiple matching strategies exist [337], but may have to employ different equivalence notions that underlie the matching of events [256], e.g., matching based on equivalent machine identifiers for multiple sensors attached to a machine in a production facility.

Fourth, *data quality utilization* limits the solution space to methods that not only acknowledge the existence of data quality issues such as missing data in their design, but also improve the prediction by actively exploiting the existence of data quality issues. [190], for example, develops a self-supervised technique to fully utilize electronic health records that inherently lack a certain type of label.

Conjointly, 15 of the 16 discussed requirements (excluding the *prediction timeliness* requirement) serve as the assessment scheme for existing work on event prediction methods in Section 4.

4 ASSESSMENT OF EXISTING EVENT PREDICTION METHODS

This section presents the analysis of 260 papers from the literature compilation in Figure 2. Each paper is analysed with respect to the 15 requirements contained in the assessment scheme introduced in Section 3.2, resulting in an overview for each requirement depicted in Figure 6. The goal of the analysis is to understand the current status of event prediction methods from a systems perspective (cf. Section 1 and Section 3) and to pinpoint open research challenges with their corresponding research directions (cf. Section 5). The results are presented overall in Section 4.1 with details per type of requirement in Section 4.2 - Section 4.4.

The assessment of the requirements uses an ordinal scale: + means that the requirement is met (for the explainability requirement, this assessment corresponds to "white box" cf. Section 3.2), ~ means that the requirement is partly met (for the explainability requirement, this assessment corresponds to both "white box" and "black box") and – means that the requirement is not met (for the explainability requirement, this assessment corresponds to "black box").

4.1 Overall Results

The results for each assessment requirements in Figure 6 give a nuanced view on research progress in the field of event prediction methods, as the overall article shares vary across the assessment requirements. By applying a threshold $\lambda = 20\%$ (corresponds to 52 articles) on the ~ assessment result, we get two sets of requirements: One set that contains requirements with article shares above the threshold (i) and another set that contains requirements below the threshold (ii). In set (i), existing work has proposed methods that meet the requirements *probabilistic prediction*, *RCA support*,

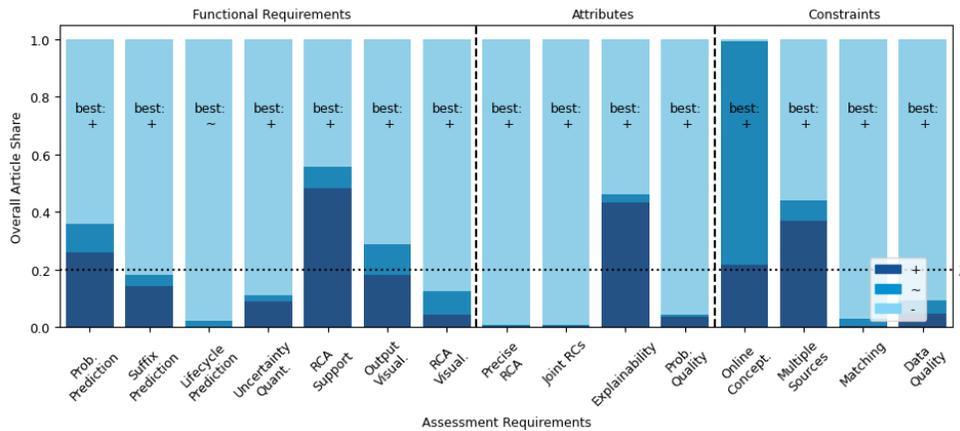


Fig. 6. Assessment results for all articles per requirement.

output visualization, explainability, online conceptualization and multiple sources. The majority of methods meeting those requirements emphasize the need for monitoring, causality, explanation, and visualization and acknowledge that relevant data is typically distributed over multiple data sources. In set (ii), existing work misses the requirements *suffix prediction*, *lifecycle prediction*, *uncertainty quantification*, *RCA visualization*, *precise RCA*, *joint RCs*, *probabilistic quality*, *matching* and *data quality* to a large extent. Despite the very low shares of articles meeting the requirements *precise RCA*, *joint RCs*, and *matching*, still some approaches fully meet them (+). *Lifecycle prediction* is the only requirement with a ~ as the best assessment.

The distribution of the + assessment count for each paper is presented as a boxplot in Figure 7. It reveals that the majority of papers focuses on one to three of the assessment requirements, i.e., the design of event prediction methods is typically aimed towards a few, particular characteristics. Although a method design with a clear focus is beneficial during method design, the result leaves the problem of system design and combining various characteristics of methods for meeting more requirements to the practitioner that wants to use the method. Moreover, the distribution shows that the mostly positive best assessment in the requirements-view is due to various papers, i.e., there is no single paper that is close to the best possible assessment.

In the following, we aim to support a more holistic development of event prediction methods meeting more requirements by illustrating the method’s feature(s)² for each requirement with an example from existing work on each requirement. The examples are selected based on how straightforward, concise and representative their features for meeting the requirements are and how well they reflect the diversity of prediction goals and application domains. The illustration shows how key design aspects are responsible for features of the method that are in turn responsible for meeting the requirement. Please note that we overload the meaning of features as the encoded input data (cf. Definition 2.2) and

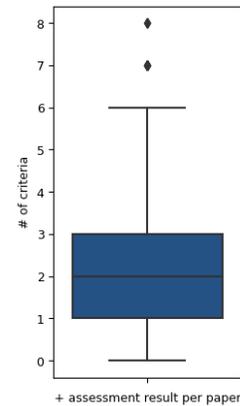


Fig. 7. Distribution of + assessment result per paper.

²Some features are illustrated with definitions or equations from the original work that is cited at the beginning of the example, i.e., if the illustration states a definition or equation, then it is taken from the original work and its key part for illustration is extracted and adapted for an as consistent as possible presentation using our survey’s notation.

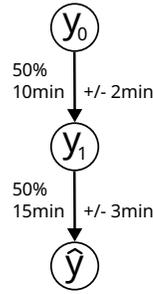


Fig. 8. An event graph for events y_0 , y_1 and \hat{y} that follow each other in system logs of a supercomputing cluster node [98]. The probability of following, the average time delay and the standard deviation of time delay is added for each relation between events.

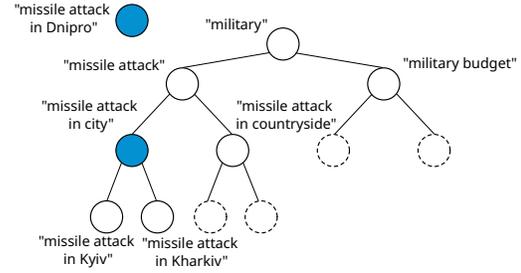


Fig. 9. A hierarchy of most general to most specific observed events [245]. On receiving a current event of a missile attack in Dnipro, the most specific event in the hierarchy that semantically matches the current event is used for prediction.

the properties of a method that are responsible for meeting a requirement. The presentation of examples is structured along the three groups of requirements: functional requirements, attributes and constraints. It is accompanied by an analysis of how the requirement may be related to other requirements and a discussion of the respective approaches.

4.2 Results for Functional Requirements

There are seven requirements that are functional for the event prediction method (cf. Figure 6).

Probabilistic prediction. [98] predicts the time and event failure type of high-performance computing cluster nodes by extracting event graphs from system logs and computing the confidence of the correlation between events, the average time delay between events and its standard deviation. Figure 8 shows a small, exemplary event graph with three events y_0 , y_1 and \hat{y} . For a *probabilistic prediction*, the event prediction method in [98] predicts the probability of event \hat{y} that follows event y_0 and y_1 with Bayes law to be $50\% * 50\% = 25\%$ and the time of event \hat{y} to be 25 minutes +/- $(2 * 4 \text{ minute} + 2 * 3 \text{ minute}) = 14 \text{ minutes}$ with 95% probability after y_0 has occurred.

Leveraging the event graph, Bayes law and the assumption of normally distributed time delays leads to a straightforward, probabilistic conceptualization of event prediction. For the same reasons, the prediction can be traced back to one or a set of root causes in the event graph such that the method meets the requirements of *RCA support*. Furthermore, the simplicity of the method helps domain experts to understand its output, yet may fail to perform well when facing complex dependencies between events in multiple dimensions, e.g., a patient's clinical history and future treatment outcome. This indicates a trade-off between simplicity of the probabilistic conceptualization and its applicability to complex monitored systems, their application domains and corresponding prediction goals.

Methods with a probabilistic prediction all conceptualize the method with conditional probabilities, Bayesian or Markovian settings, but differ in their degree of statistical rigor. Statistical rigor captures the number of assumptions on the distribution of the input data, how restraining the distribution assumptions are and how formal the derivation of the event prediction method is given those assumptions. For example, [12] exhibits a high degree of statistical rigor, as it features a high number of assumptions on the distribution of the data that restrain it to a large degree (e.g., the input data is the result of a Gaussian autoregressive process of the second order) and the whole event prediction method is formally derived from those assumptions. [98] exhibit a medium degree of statistical rigor, as they assume normally distributed time delays and apply Bayes law, but do not formally derive the overall event prediction method. [236]

exhibits a low degree of statistical rigor, as they explicitly aim at designing the event prediction method to have no assumptions and do not formally derive any part of the method.

Suffix prediction. [142] predict the full sequence of future events for an ongoing manufacturing cycle, i.e., all the events that are likely to occur until the production is complete, with the goal of predicting key performance indicators such as product quality (the prediction goal). To the end of *suffix prediction*, [142] assumes that the future progress of the ongoing cycle s with length n can be similar to the progress of k historical cycles l_1, \dots, l_k after n events of each historical cycle l_i has been observed. Based on this assumption, [142] apply k-Nearest-Neighbor clustering with Euclidean distance on the n -length prefix of historical cycles and the ongoing cycle resulting in k suffixes for the ongoing trace. Then, [142] apply a support vector machine classifier on the k suffixes to predict the key performance indicator. At last, the k predicted key performance indicators are aggregated into a single indicator.

Although this indirect basic technique can show the operations manager in the production facility additional information on how the current cycle will progress, this method likely fails to accurately predict for a production line with hundreds of thousands of different cycle variations. In contrast to [142], many other methods such as [179] or [73] predict the suffix by repeatedly applying a next event prediction method. Although this can be done for any event prediction method, the major challenge of looping through events that are likely has to be tackled by methods repeatedly applying the event prediction method for *suffix prediction*.

Lifecycle prediction. [179] predict the next events of business processes by learning a recurrent neural network that takes multiple event attributes into account. Accordingly, the event prediction problem is stated for an ongoing process instance $y = \langle (e_1, a_1^1, \dots, a_1^m), \dots, (e_n, a_n^1, \dots, a_n^m) \rangle$ with event activities e_1, \dots, e_n and event attributes a_1^1, \dots, a_n^m as predicting the next event $(e_{n+1}, a_{n+1}^1, \dots, a_{n+1}^m)$ of the ongoing process instance s . Hence, [179] can predict lifecycles of events, since the lifecycle of an event is an attribute of the event. Nevertheless, lifecycle carries special semantics for event prediction, as, for example, an *abort* lifecycle event for the delivery activity of a logistics company signifies that the *end* will not occur at all and, therefore, the delivery will fail [256]. Also, the lifecycle determines the duration of the activity recorded through multiple events, e.g., an activity paused once for 5 minutes has a duration of 5 minutes lower than the time between its *start* and *end*. For prediction goals that are evaluated on the duration, e.g., efficiency of the resource executing the activity, the special semantics of the lifecycle has to be taken into account. Consequently, the prediction method should not stop at predicting the lifecycle as an attribute, but incorporate its semantics.

Similarly, the other proposals partly meeting lifecycle prediction conceptualize event prediction with multiple, unspecified event attributes and do not incorporate lifecycle semantics. If the data source for the evaluation does not provide lifecycle information, this should not be taken as the reason for excluding it in a method design, as this would not allow the method to be generally applied to data sources with event lifecycle information. Due to the importance of lifecycle information for prediction, if the data source does not provide lifecycle information, researchers should recommend the additional recording of this information to those data sources.

Uncertainty quantification. [320] predict the time-to-event for treatment outcomes of patients in clinics by extracting features with recurrent neural networks and learning a Parametric Predictive Gaussian Process (PPGP) Regressor in a survival analysis setting. The combination of the PPGP Regressor and survival analysis results in the survival function:

$$S(y_i | \mathbf{h}_i) = 1 - F \left(\frac{y_i - \mu_{\mathbf{f}}(\mathbf{h}_i)}{\sigma_{\mathbf{f}}(\mathbf{h}_i) + \sigma_{\text{obs}}} \right)$$

where S is a survival function, y_i the logarithm of the time-to-event for patient i , \mathbf{h}_i the latent representation extracted by the recurrent neural network, F the normal cumulative distribution function, $\mathbf{f} \in \mathbb{R}^n$ a vector of Gaussian process

function values, $\sigma_f^2(\mathbf{h}_i)$ the input-dependent predictive variance and σ_{obs}^2 the input-independent observational noise for the logarithmic time-to-event y_i . The corresponding objective that [320] propose puts more weight on the input-dependent predictive variance $\sigma_f^2(\mathbf{h}_i)$ than earlier proposals that combine Gaussian Processes and survival analysis. Hence, the formulation of survival analysis with PPGP Regressors and the corresponding uncertainty-aware objective not only quantifies predictive variance, i.e., epistemic uncertainty³, and observational noise, i.e., aleatoric uncertainty, but also strengthens the positive relationship between predictive variance and prediction error. Consequently, the less confident the uncertainty-aware event prediction method is, the less accurate its predictions are.

In addition to quantifying the uncertainty of the prediction, appropriately integrating it to the objective of the event prediction method yields a desirable relationship between uncertainty and prediction quality. The information that more confident predictions correspond to more accurate predictions is valuable to practitioners [131]. This information likely results in more trust towards the method. By further differentiating between epistemic and aleatoric uncertainty, the quantified uncertainty also shows whether a currently low confidence could be improved with more data.

Existing proposals mostly quantify uncertainty by means of a probabilistic conceptualization that allows to inherently estimate uncertainty as some form of variance in the method and, thus, focuses on the method, e.g. [320]. Depending on the degree of statistical rigor (cf. *probabilistic prediction*), these estimates are more or less justified by statistical theory. Another option is to extrinsically quantify uncertainty by approximating it using, e.g. characteristics of the input data. [57] propose an uncertainty metric that also considers how many activities of a business process instance have been observed and what time has elapsed since the last activity has been observed. The rationale for their extrinsic uncertainty quantification is that more and more recent data on the monitored system relate to a more certain prediction.

RCA support, output visualization and RCA visualization. While [98] apply Bayes law on descriptive statistics of the data without a statistical analysis formulation, [169] combine decision rules with Bayesian analysis into Bayesian Rule Lists (BRL):

```

if antecedent1 then  $y \sim \text{Multinomial}(\Theta_1)$ ,  $\Theta_1 \sim \text{Dirichlet}(\Phi + \mathbf{N}_1)$ 
:
else if antecedentm then  $y \sim \text{Multinomial}(\Theta_m)$ ,  $\Theta_m \sim \text{Dirichlet}(\Phi + \mathbf{N}_m)$ 
else  $y \sim \text{Multinomial}(\Theta_0)$ ,  $\Theta_0 \sim \text{Dirichlet}(\Phi + \mathbf{N}_0)$ 

```

where antecedents are well-formed formulas with c_i , $i \in \{1, \dots, m\}$ atomic propositions over the feature vector that do not overlap, y is the prediction goal value, Θ_i are parameters of the respective distribution, Θ_0 a default rule parameter for observations that do not satisfy any of the antecedents, Φ a prior of the prediction goal values and \mathbf{N}_i the respective observation counts satisfying antecedent i . By limiting the parameters m and c_i to small integers as well as deriving a mean point estimate and credible interval for the prediction goal value y , BRLs represent a simple, interpretable prediction model. Potential root causes are represented as antecedents of the BRL (*RCA support*). The prediction output and the RCA are visualized by showing the BRL and traversing its rules from top to bottom given an observation. [169] compares this BRL to a medical score that is frequently used to predict the stroke risk by physicians, identifies antecedents with known root causes or risk fusers and concludes that the BRL is as interpretable as the medical score, while improving the accuracy.

Methods meeting all three requirements *RCA support*, *output visualization*, and *RCA visualization* are designed in their functionality to support the user in understanding the method and its prediction. A simple prediction model as

³Model uncertainty does not exist due to an implicit assumption that the true predictor is part of the chosen model hypothesis space [131].

in [98, 169] underlying the event prediction method support the user in tracing the prediction back to its root causes. This meaning of simplicity is captured by the "white box" assessment of *explainability*, but it is not the only sufficient condition for meeting *RCA support*, e.g., a hybrid basic approach can still support RCA in spite of a "black box" model due to the generative part of the model [181]. Due to a lack of a widely accepted definition on *explainability* (cf. Section 3.2), it is not clear whether further relationships with root causes exist. Considering visualization, some methods present a straightforward way of visualizing the output or RCA as in [169], while others need specifically designed visualization techniques, e.g. neural networks.

4.3 Results for Attributes

There are four requirements that are attributes of the event prediction method (cf. Figure 6).

Precise RCA, joint RCs and Explainability. [245] predict future events that can be caused by a current news event. To that end, they choose an aggregate semantic event representation for an event $e = (P, O_1, \dots, O_4, t)$, where P is a state or temporal action exhibited by the event's objects, O_1 a set of users, O_2 a set of objects on which the action P was performed, O_3 a set of instruments utilized by the action, O_4 a set of locations and T a timestamp. Given a set of historic events $\{\langle e_1, g(e_1) \rangle, \dots, \langle e_n, g(e_n) \rangle\}$ for an unknown causality function g mapping historic cause event to its effects, [245] aim to approximate g by learning a causality graph of events with the help of existing ontologies on actions such as VerbNet [150] and on objects such as the LinkedData ontology [22].

Using existing ontologies, the method can evaluate the precision of identified root causes (*precise RCA*). For identifying *joint RCs*, the method proposes a generalization event by generalizing over its actions and objects. The result is a hierarchy that detects that similar root causes are in fact joint root causes. Figure 9, for example, depicts a generalization hierarchy of observed events that identifies similar root causes as joint, more general root causes. Since the prediction is computed solely on the causality graph through matching the current event with an existing event in the causality graph (denoted in green in Figure 9) and applying a prediction rule associated with the event, a user can traverse the predicted event back to its matched, historic event. Thus, the method employs a "white box" model (*explainability*).

Despite their existence, ontologies are seldomly used in event prediction. With the help of ontologies, the method can establish a concept of causality and meaning. Moreover, event prediction methods rarely exploit that events are related by a semantic generalization relationship. However, other semantic relationships between events are exploited by recent methods, e.g. the disease co-occurrence [188] or compatible related treatment outcomes relationships [103].

Probabilistic Quality. [309] predict crime frequencies in the spatio-temporal domain by combining variational autoencoders and sequence generative neural networks. Hence, a predicted crime frequency is $\hat{y}_{i,j,k}^{(t)}$ for the geographical grid indexes i, j , crime type k in the time slot t . To evaluate these probabilistic predictions, [309] first normalize the true and predicted crime frequencies:

$$p_{i,j,k}^{(t)} = \frac{y_{i,j,k}^{(t)}}{\sum_{i=1}^M \sum_{j=1}^N y_{i,j,k}^{(t)}}, \quad \hat{p}_{i,j,k}^{(t)} = \frac{\hat{y}_{i,j,k}^{(t)}}{\sum_{i=1}^M \sum_{j=1}^N \hat{y}_{i,j,k}^{(t)}}$$

and then compute the Jensen-Shannon divergence with laplacian smoothing:

$$D_{JS}(P, \hat{P}) = \frac{1}{2} D_{KL}(P \parallel Q) + \frac{1}{2} D_{KL}(\hat{P} \parallel Q)$$

where $Q = \frac{1}{2}(P + \hat{P})$ is the average of true and predicted probability. Next to the Jensen-Shannon divergence, there exist at least 200 further scores for evaluating probability estimates [41]. Thus, analysing its properties with respect to

event prediction and proposing a standardized set of scores goes beyond the scope of this survey. For this survey, the important point is that the evaluation is done using a metric that scores probability estimates, as is the case for [309].

For evaluating probabilistic predictions, the predictions must come with probability estimates. Thus, meeting the requirement of *probabilistic quality* implies meeting *probabilistic prediction*. Yet, these two requirements are not equivalent, because many articles do not report results of scoring probability estimates. While roughly 25% of the 260 articles propose methods meeting *probabilistic prediction*, less than 5% evaluate the predicted probabilities with an appropriate score (cf. Figure 6).

4.4 Results for Constraints

There are four requirements that are constraints for the event prediction method (cf. Figure 1).

Online conceptualization. [248] predict civil unrest events across ten Latin American countries through a continuous, automated system that runs 24/7 and constantly processes events coming from various open sources such as social media. Consequently, the event prediction method consisting of an ensemble of methods is proposed to continuously learn from daily data, e.g., a logistic regression models is learned using daily tweet counts while a rule-based method detects keywords contained in social media posts. The system has a throughput of 200-2000 messages/sec, predicts roughly 40 events/day and can ingest up to 15 GB of messages on a given day. Therefore, it features an *online conceptualization* and can monitor the ten Latin American countries for social unrest events.

Given its daily cycle and the ensemble of prediction methods, a daily, full retraining of the prediction models is feasible. However, a full retraining may become infeasible for event prediction methods in light of updating cycles not longer than a few minutes. For this reason, [258] investigate strategies for updating the prediction model that go beyond full retraining; Do nothing, i.e., no update; retraining with no hyperparameter optimization, i.e., a lightweight retraining; full retraining, i.e., train on all available events; and incremental update, i.e., applying incremental learning algorithms. The results show that full retrain and incremental update are the best strategies for predicting business process events.

Still, not all prediction models allow for incremental updates through incremental learning algorithms. Thus, [210] investigates six strategies to handle updates to the prediction model by means of data selection strategies: Baseline strategy, i.e., no update to the training data; cumulative, i.e., update training data on every new event; non-cumulative, i.e., update training data on every new event by keeping the k most recent events; ensemble, i.e., non-cumulative and keeping all models for ensemble prediction; sampling, i.e., update training data by sampling all available events; and drift, i.e., non-cumulative with drift detection such that only training data after a drift is selected. The results show that the ensemble strategy performs best for predicting business process events.

Despite these pointers to suitable strategies for updating prediction models, a best strategy for all use cases cannot be determined due to a case-dependent trade-off between the resources required to improve the quality of prediction through updating and its benefits.

Multiple sources. [4] predict the time-to-event for future failures of engineering system devices. Sensor data $X_p \in \mathbb{R}^{d \times c_p}$ from d sensors for each device p observed until time c_p and event data $y_p \in \{0, 1\}$ is used to predict the time-to-event T for the future failure $y_p = 1$ of device p . For prediction, [4] propose a multi-task learning framework based on neural networks with a task p for each device. Hence, p data sources are used in the event prediction method (*multiple sources*) and the integration of these data sources is implicitly learned by the neural network within the multi-task learning framework.

We can distinguish two approaches to data integration. The *implicit* approach to data integration combines the data integration with the learning of a prediction model in the event prediction method such that the data integration is tightly coupled with the event prediction method, e.g., the data integration of the p devices is implicitly learned by the neural network in [4]. The *explicit* approach to data integration separates data integration from the event prediction method such that both of them become interchangeable. To that end, the explicit approach implements necessary functionality for data integration (cf. input component in Section 3.1) before the event prediction method is applied to the data. [248] not only illustrates the *online conceptualization*, but also the explicit approach to data integration. Many different sources such as NASA satellite meteorological data, Bloomberg financial news and Twitter’s public API are used. Each source is ingested by a specialized routine to convert the data input to JSON and add identifiers. Before the event prediction method is applied, the JSON input is enriched through, e.g. geocoding, data normalization and entity extraction. Consequently, the event prediction method does not need to learn how it can integrate the data. In comparison, the implicit approach intertwines the input component of a PCM system (cf. Section 3.1) with the prediction component, whereas the explicit approach keeps them separated. The former has the advantage, that it does not need to design data integration functionalities, but may experience worse performance for heterogeneous data sources and consuming more resources for training. The latter has the advantage, that it has direct control and knowledge on the specific data integration routines, but comes at the cost of more design and maintenance effort.

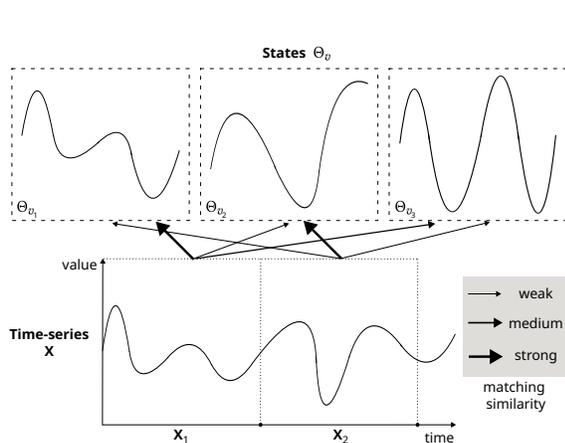


Fig. 10. Time-series X is segmented into X_1 and X_2 . Each time-series segment is recognized with states Θ_{v_1} , Θ_{v_2} and Θ_{v_3} [123]. Recognized states and the similarities are used in the event prediction method proposed in [123] instead of the original time-series.

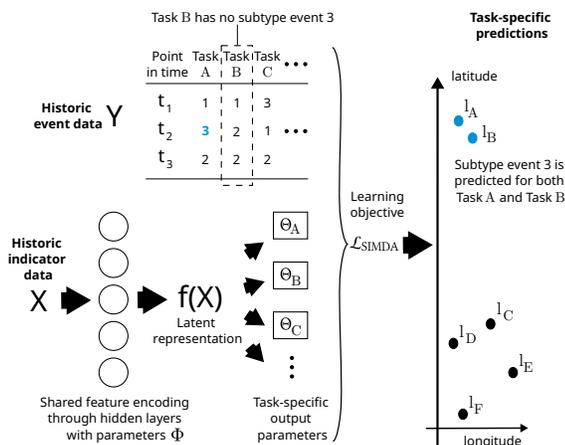


Fig. 11. Spatial Incomplete Multi-Task Deep Learning (SIMDA) Framework [106]. Despite no recorded subtype event 3 in the historic event data Y for task B , SIMDA allows to predict subtype event 3 in task B that corresponds to location l_B , since location l_A is geographically close to location l_A and location l_A has recorded subtype event 3 in the historic event data of task A .

Matching. [123] predict a future event in a time-series sequence, e.g. a future anomalous watt-hour meter clock event of the State Grid of China in weekly sensor readings. To that end, a future event $y_{t+1} \in \mathbb{Z}$ is predicted based on historic events y_t and T segments $X_t \in \mathbb{R}^{\tau \times d}$ of the time-series sequence $X \in \mathbb{R}^{N \times d}$ with length τ :

$$\langle X_{1:T}, y_{1:T} \rangle = \{(X_1, y_1), \dots, (X_T, y_T)\}$$

Before feeding the historic data $\langle X_{1:T}, y_{1:T} \rangle$ into a neural network, the proposed event prediction method recognizes representative time-series patterns called *states* and denoted as $\Theta_v \in \mathbb{R}^{r \times d}$ for segments of the data (cf. Figure 10). Hence, redundant or very similar time-series patterns from multiples sources are recognized by the same state (*matching*).

[123] is the only method proposed that features an explicit matching mechanism for data coming from multiple sources. Other proposals for matching [2, 121, 143, 166, 177, 248, 307, 334] are not explicitly including the mechanism in their method.

Data quality. [106] predict the location of event subtypes, e.g. instead of predicting the air pollution of cities as future events, the respective air pollutant subtype (Carbon monoxide, nitrogen dioxide, fine dust pollution etc.) is predicted. While the predicted event subtype allows for more fine-grained actions, e.g. allocating appropriate resources per air pollutant subtype, incomplete, historical data for event subtypes in many locations becomes a major data quality challenge for predicting event subtypes for all locations.

Figure 11 depicts the data quality challenge for predicting event subtypes and the proposed method, Spatial Multi-task Deep leArning (SIMDA), to overcome the challenge. Each depicted prediction task A, B and C corresponds to a geographical location $L = \{l_A, l_B, l_C, \dots\}$. Historic event data $Y_{l,t} \in S = \{1, 2, 3, \dots\}$ and d -dimensional, historic indicator data $X_{l,t} \in \mathbb{R}^{1 \times d}$ for date t is available for each location $l \in L$. However, for the location l_B corresponding to task B , no event subtype $s = 3$ was recorded, e.g. a city in the past has not recorded fine dust pollution (cf. Figure 11). Hence, the specific model for task B will not predict event subtype $\hat{y}_{l_B, \tau} = 3$ at location l_B for $\tau = t + p, p > 0$, although the geographically close location l_A in task A shows that event subtype $s = 3$ has occurred. Since geographical heterogeneity across all locations does not allow for a single task approach, learning from other locations such as l_A for location l_B has to be achieved differently. On account of the first law of geography stating that geographically closer locations will be more similar to each other than farther locations [61], [106] state that two close locations $i, j \in L$ have similar conditional probabilities for an event subtype s :

$$P(Y_{i,t} = s | X_{i,t}) \approx P(Y_{j,t} = s | X_{j,t})$$

This relationship is exploited to formulate a SIMDA objective that enforces event subtype patterns to be similar for geographically close tasks:

$$\mathcal{L}_{\text{SIMDA}} = \mathcal{L}_d(\Phi, \Theta) + \frac{\beta}{2} \sum_l^L \sum_{s,r}^{S^2} \|f(X_l)(\Theta_{l,s} - \Theta_{l,r})^T - \frac{1}{N_l} \sum_c^L \text{adj}(l, c) f(X_c)(\Theta_{c,s} - \Theta_{c,r})^T\|_2^2$$

where $\mathcal{L}_d(\Phi, \Theta)$ is the general multi-task deep learning objective with d dimensions, Φ the weight parameters of the shared hidden layer, Θ the weights of the task-specific output layer, β a hyperparameter, $f(\cdot)$ the computation of the shared hidden layers, $\Theta_{l,s}$ the weights of task l for predicting event subtype s , $N_l = \sum_c^L \text{adj}(l, c)$ the normalization term for location l , and $\text{adj}(\cdot, \cdot)$ some physical distance function. Hence, [106] propose to add a regularization term to the general multi-task deep learning objective $\mathcal{L}_d(\Phi, \Theta)$ that enforces geographically close locations i, j to have similar event subtype patterns $X_i(\Theta_{i,s} - \Theta_{i,r})^T \approx X_j(\Theta_{j,s} - \Theta_{j,r})^T$. For the example as depicted in Figure 11, this allows SIMDA to predict fine dust pollution $s = 3$ for location l_B through task B , as the geographically close location l_A exhibits a lot of fine dust pollution.

Analogous to [106], methods that actively utilize data quality issues so far have exploited the following semantic similarity relationships between components of the monitored system (e.g., close locations, comparable patients etc.) to improve the prediction while keeping the component-level granularity in the prediction model (e.g. a task for each

location): semantic similarity based on proximity [105, 106, 339, 343], hierarchy of geographical regions [339, 343], logging granularity of cyber system host sources [319], patient disease histories [190, 236, 271], hierarchy of medical codes [190], hierarchy of mobile health study participants [68], individual units of engineering systems [67], feature missingness patterns [304] and structural tweet content [338]. In contrast to preprocessing techniques such as imputation for missingness, these proposals make the method aware of the data quality and base the awareness on the semantic similarity relationships.

Since data quality issues should lead to more uncertain predictions, this requirement is related to *uncertainty quantification*. For example, [271] propose a method that abstains from predicting in case of high uncertainty of the prediction due to missingness of data. Hence, the missingness of data has a direct impact on the prediction in their proposed method. All in all, the link between data quality and uncertainty can be used to guide the prediction (e.g., no prediction in case of high uncertainty due to data quality issues) or the data quality issue can be alleviated by exploiting semantic relationships leading to more certain predictions.

4.5 Summary

Overall, event prediction approaches broadly support the requirements for building a PCM system concerning the input and output of the prediction method as well as its evaluation and understanding (cf. Figure 5). Looking more closely at the requirements support, the following conclusions can be drawn:

- (1) So far, existing approaches have been fragmented with respect to research area (e.g., event prediction and PPM) as well as with respect to the application area (cf. Figure 1).
- (2) The concept of the PCM system enables the integration of disparate event prediction approaches and applications.
- (3) Event prediction approaches support requirements through a combination of the prediction goal and event prediction method.
- (4) None of the approaches supports event life cycle prediction.
- (5) None of the approaches supports all requirements; most of the approaches support 1 – 3 requirements (cf. Figure 7) and at most 8 out of 16 requirements.

Conclusions 1 – 5 underpin the importance of the PCM system concept for holistic event prediction and point to open challenges and research directions, which will be discussed in Section 5.

5 OPEN CHALLENGES AND RESEARCH DIRECTIONS

Section 4 shows the considerable progress of event prediction methods regarding requirements of a PCM system. In spite of these advancements, the landscape of existing work is fragmented and faces the following open challenges with potential future research directions.

5.1 Holistic Event Prediction Method

Challenge: No event prediction method simultaneously meets all requirements. Hence, selecting a single event prediction method leaves us with the necessity of trading off various sets of features with one another. The challenge is to develop event prediction methods that support more or all requirements by the method's respective features.

Research direction: For a holistic approach to method development, future research can either combine existing features from various methods into a single method, develop new solutions to the respective existing problems for a single method or combine existing methods and, thus, their features in a generic framework. Independent of the chosen option,

a conceptual model of event prediction that identifies the systematic relationships between application domains, domain knowledge, prediction goals, input data, feature engineering, prediction methods and the action space is desirable. This conceptual model particularly represents our understanding on how an application domain, the existing domain knowledge and given prediction goals require a certain set of data sources, a certain set of features engineered on the data, appropriate prediction methods (cf. Figure 3) and the possible action space. Such a model extends the structural system perspective on event prediction and its surrounding components embodied by the PCM system (cf. Figure 4) and the methodological perspective on event prediction in [337] with a behavioral and operational system perspective.

5.2 Semantics, Knowledge and Explainability

Challenge: Event prediction aims at anticipating the future of the monitored system by means of algorithms. Monitored systems come from a diverse range of application domains and, thus, have a diverse range of semantics. At some point in the PCM system, the algorithms used to develop event prediction should take the semantics, e.g. of the event lifecycle, into account. The same applies to existing domain knowledge. Aside from potentially positive effects on accuracy, the way semantics and knowledge are taken into account determines the explainability of the method and its generality: If the method is very abstract and generic, it is typically not explainable to the domain expert, whereas a very concrete and domain-specific method is typically explainable, but does not generalize. The challenge is to shift the trade-off between explainability and generality and develop new ways to integrate semantics and knowledge in the method for an improved explainability while maintaining generality.

Research direction: Starting with a clear definition of explainability for event prediction, e.g. is it rather a counterfactual or the more strict causal definition [254], and the necessary content type, communication means and target group of the explanation [34], future research can evaluate the correctness of explanations. Explanation-guided learning [104] demonstrates promising approaches to explainability and correctness evaluation, yet it pre-determines the way of how the method integrates semantics and domain knowledge by stating them as explanation supervision and regularization in the learning objective. Other or additional ways of integration could be parametrization, feature engineering or a certain hypothesis space for explainable models. It is highly beneficial to explore various combinations of integration and test for generality of the method such that we can improve our understanding on how semantics and domain knowledge can be used for explainability while maintaining generality.

5.3 Flexibility and Robustness

Challenge: Considering the heterogeneity of application domains, data sources and prediction goals, event prediction methods must find a balance between flexibility and robustness. On the one hand, they have to be flexible with respect to (i) domain-specific properties and requirements, e.g. a very dynamic, clinical environment in the healthcare domain with a particularly strong requirement on uncertainty vs. a relatively stable environment of a standardized goods manufacturing facility with a relatively weak requirement on uncertainty, (ii) the data properties and quality issues of multiple data sources, e.g. different granularities of the data such as city- vs. country-level and missingness of data, and (iii) prediction goal properties, e.g. a single, stable prediction goal such as "treatment outcome of a patient is positive" vs. multiple, dynamic prediction goals such as the set of regulatory constraints a bank's business processes have to adhere to. On the other hand, event prediction methods have to be robust with respect to adversarial attacks and/or noise of the input data [57, 153, 337], since event prediction in a PCM system has a direct real-world consequence through the action that the user chooses.

Research direction: One way to deal with the flexibility challenge is to limit the scope of the method to a certain problem

space for which flexibility is not required anymore. So far, this approach dominates research on event prediction. Although this approach can solve the challenge by removing it from the equation to a large extent, it results in a very fragmented set of event prediction methods and transfers the challenge to the user. Future methods should abstain from definitions that simplify the problem in this way. For (i) domain-specific properties and requirements and (ii) data properties and quality issues existing work supports the required flexibility (cf. assessment for *uncertainty quantification*, *online conceptualization* and *multiple sources* in Section 4). Thus, the combination of these is a promising starting point for future work on meeting flexibility for (i) and (ii) together. While [193] called for flexibility regarding various sets of prediction goals, flexibility for (iii) prediction goal properties is usually still abstracted from or left unmentioned. Considering the multi-objective nature of event prediction [337] and the abundance of regulatory requirements on monitored systems such as banks [99], clinics [29, 47] or manufacturing facilities [119], event prediction methods that are flexible with respect to prediction goal heterogeneity are highly beneficial. Since a more flexible event prediction leaves more room for adversarial attacks, research on flexible event prediction should study how these mechanisms interact with adversarial attack models. With respect to noise, methods are desirable that can reliably distinguish variances in the input data that require flexibility from noise that should be captured as aleatoric uncertainty.

5.4 User Interface

Challenge: As event prediction research focuses on the method and its rather technical evaluation, it often does not provide a simple and clear user interface of relevant output. Moreover, probabilistic predictions with uncertainty estimates, multiple prediction goals, root causes and potential actions aggravate the challenge to present the output in a simple and clear way to the user. Although the user interface corresponds to the output component of a PCM system that is separated from the prediction component, the method design should already have the subsequent user interface in mind to ease its design and implementation, e.g., by suggesting certain visualization techniques. Lastly, some methods have started proposing the integration of prediction with decision theory to include actions and their impact [28, 271, 305], but these are goal-dependent and domain-specific and, thus, cannot be easily transferred to other goals and application domains. Furthermore, [28, 271, 305] lack to provide how the additional information should be integrated to present the output to the user.

Research direction: By adopting principles of user-centred design [113], future research can explore means of presenting and visualizing the complex output of event prediction and the PCM system to the user. This challenge should not be taken lightly, as it significantly determines the adoption of the method by users and may affect the user's trust in the system. Research that incorporates actions through a decision theoretic framework further supports the user in deciding what to do based on the anticipated future. By allowing for parametrizing the action space, future work on event prediction can increase the flexibility of the method (cf. Section 5.3) and enables the user in setting the action space. The development of a comprehensive user interface for a PCM system that streamlines the relevant information to the user and takes subsequent actions into account is key for building trust and increasing the accessibility for users.

5.5 Evaluation

Challenge: While [337] presents the evaluation design with respect to matching predicted with real events and metrics of effectiveness for event prediction, it neither considers probabilistic metrics of effectiveness nor the performance in terms of training and prediction time. However, both are crucial for a standardized and valuable evaluation of event prediction.

Research direction: [41] reviewed 201 probabilistic metrics of effectiveness that are candidates for event prediction.

Both an analysis as well as standard proposal for event prediction is needed. This proposal can be directly applied in a comprehensive, empirical comparison of existing methods within comparable classes of our taxonomy for event prediction methods (cf. Figure 3). With respect to the time performance, the comparison can utilize appropriate benchmark case studies to additionally compare the training and prediction times.

6 CONCLUSION

This work presents a comprehensive survey on event prediction methods that span multiple, disparate research areas corresponding to the nine application domains for event prediction. To bring the work on event prediction methods from these disparate research areas together, we take a systems perspective on event prediction and identify four research questions. The first question aims at a taxonomy of event prediction methods for integrating the diverse selection of event prediction methods. To facilitate the design of the taxonomy and to reflect the systems perspective, we formulate the event prediction method with an event prediction goal. For the design of the taxonomy, we additionally followed the aim of integrating existing taxonomies for event prediction. After the comprehensive classification of event prediction methods with the taxonomy, the second question aims at designing an assessment scheme for event prediction that takes the multi-faceted nature of event prediction into account. This question leads us to leverage the systems perspective further to propose the PCM system as a decision support system for event prediction. In proposing the PCM system, we generalize ideas from the research areas PPM and CM such that the respective contributions can be mutually exchanged with other research areas for event prediction and structurally identify event prediction as a component of a decision support system. Based on the PCM system and existing work on event prediction methods, we elicit requirements for event prediction methods. The third question aims at the qualitative assessment result of existing event prediction methods with respect to the requirements. The assessment shows that not only the research areas for event prediction are fragmented, but also the event prediction methods in terms of meeting the requirements. Furthermore, the assessment illustrates how a specific combination of a prediction goal and an event prediction method are used by existing work to achieve specific requirements. The fourth question aims to derive open challenges and future research directions for event prediction given the assessment of existing work. To that end, we find five challenges and corresponding research directions for event prediction that, inter alia, cover a holistic approach to event prediction methods as a direct consequence of the PCM system interpretation (cf. Section 5.1).

ACKNOWLEDGMENTS

This work has been partly funded by the Austrian Research Promotion Agency (FFG) via the “Austrian Competence Center for Digital Production” (CDP) under the contract number 854187 and by the Deutsche Forschungsgemeinschaft (DFG) under the contract number GRK 2201. This work has been supported by the Pilot Factory Industry 4.0, Seestadtstrasse 27, Vienna, Austria.

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A CLASSIFICATION OF EXISTING WORK

In the following, we present the classification of existing work into our taxonomy for event prediction methods (cf. Figure 3) as additional material for the electronic supplement. The classification is valuable for orientation by practitioners and searching for related work in other application domains by researchers, but is not necessary in its entire extent (cf. Table 3 - Table 6) for the main findings of this survey.

Table 3. Time event prediction article classification with abbreviations for classes as highlighted in bold in Figure 3 and the superscript for domains as introduced in Figure 2.

Output Repr.	Basic Model	Basic Techn.	Sources
Occ	Inf	Dir	[78] ^E [182] ^E [218] ^I [269] ^N [187] ^E [335] ^I [17] ^E [144] ^E [262] ^B [175] ^B [324] ^B [42] ^E [168] ^B [191] ^B [303] ^B [164] ^B [233] ^B [282] ^B [274] ^B [35] ^B [261] ^B [210] ^B [96] ^B [296] ^B [149] ^B [257] ^B [226] ^B [202] ^B [117] ^B [101] ^B [90] ^B [268] ^B [70] ^B [197] ^B [258] ^B [203] ^B [232] ^B [306] ^B [185] ^B [312] ^B [206] ^B [289] ^B [196] ^B [212] ^B [173] ^B [321] ^E [45] ^M [242] ^H [190] ^H [348] ^E [64] ^B [105] ^P [304] ^P [346] ^N
	Hyb	Dir	[133] ^E [285] ^B [189] ^H [291] ^P [188] ^H [326] ^B
		Ind	[62] ^B
	Gen	Dir	[58] ^B [129] ^I
Dis	Inf	Dir	[270] ^I [350] ^I [284] ^I [138] ^N [204] ^I [161] ^E [171] ^I [127] ^I [253] ^E [91] ^H [100] ^I [60] ^C [82] ^I [158] ^N [7] ^T [266] ^I [176] ^H [299] ^E [344] ^E [59] ^E [123] ^E [325] ^B [38] ^B [322] ^M [3] ^H [146] ^N [186] ^H [279] ^E [225] ^I
		Ind	[305] ^I [115] ^I [46] ^I [13] ^E [112] ^I [27] ^I [227] ^B [251] ^N [280] ^H [49] ^T [145] ^P
	Hyb	Dir	[50] ^N [4] ^E [102] ^B [80] ^H [343] ^P
		Ind	[181] ^E
Gen	Dir	[76] ^E	
Con	Inf	Dir	[213] ^B [183] ^E [264] ^B [317] ^B [241] ^B [19] ^B [272] ^B [328] ^B [152] ^B [223] ^B [215] ^B [300] ^B [114] ^B [25] ^B [278] ^B [81] ^C [311] ^H [217] ^M [236] ^H
		Ind	[313] ^B [301] ^B [33] ^B
	Hyb	Dir	[332] ^E [21] ^E [10] ^B [295] ^B [1] ^B [55] ^B [238] ^B [40] ^B [125] ^B [87] ^H [103] ^H [67] ^E [315] ^H [244] ^H [320] ^H [293] ^P [88] ^E
		Ind	[271] ^H [259] ^B [93] ^B
Gen	Dir	[12] ^C [92] ^B [221] ^B	

Received TODO; revised XXX; accepted XXX

Table 4. Location event prediction article classification with abbreviations for classes as highlighted in bold in Figure 3 and the superscript for domains as introduced in Figure 2.

Output Repr.	Basic Model	Basic Techn.	Sources
Ras	Inf	Dir	[178] ^C [26] ^C [308] ^P [237] ^C
	Hyb	Dir	[339] ^P [329] ^C
Poi	Inf	Dir	[39] ^P [106] ^P
	Hyb	Dir	[220] ^M
		Ind	[341] ^H

Table 5. Semantic event prediction article classification with abbreviations for classes as highlighted in bold in Figure 3 and the superscript for domains as introduced in Figure 2.

Output Repr.	Basic Model	Basic Techn.	Sources
Cat	Inf	Dir	[163] ^B [200] ^B [89] ^B [151] ^M [5] ^B [277] ^M [347] ^M [118] ^B [352] ^B [2] ^E [97] ^I [169] ^H [298] ^I [136] ^M [122] ^M
		Ind	[53] ^B [240] ^B [231] ^B [201] ^B [74] ^B [32] ^B [156] ^B [194] ^B [134] ^B [243] ^B [234] ^B [147] ^B [66] ^P
	Hyb	Dir	[192] ^E [174] ^C
		Ind	[159] ^B
Agg	Inf	Dir	[177] ^M [331] ^M [11] ^M [14] ^M [310] ^M [336] ^M [307] ^M [128] ^M [245] ^P
		Ind	[73] ^B [179] ^B
	Hyb	Dir	[63] ^M [338] ^P
		Ind	[162] ^B
Gen	Dir	[166] ^M	

Table 6. Joint event prediction article classification with abbreviations for classes as highlighted in bold in Figure 3 and the superscript for domains as introduced in Figure 2.

Pred. Output	Output Repr.	Basic Model	Basic Techn.	Sources
Tim and Loc	Occ and Ras	Inf	Dir	[172] ^C [263] ^E
	Dis and Ras	Inf	Dir	[327] ^B [126] ^T [252] ^T [302] ^N [292] ^P [330] ^C [137] ^P
			Ind	[342] ^P [15] ^T [309] ^C [333] ^T [124] ^C [69] ^T
	Dis and Poi	Inf	Hyb	[148] ^T
			Dir	[95] ^C [23] ^P
Con and Poi	Gen	Dir	[224] ^N	
Tim and Sem	Occ and Agg	Inf	Ind	[184] ^C [323] ^C
	Dis and Cat	Inf	Dir	[142] ^B
			Ind	[43] ^E [30] ^P
	Dis and Agg	Inf	Hyb	[37] ^B [36] ^B
			Dir	[77] ^E
	Con and Cat	Inf	Ind	[52] ^B [198] ^B
			Dir	[340] ^H
	Con and Agg	Inf	Ind	[255] ^B [319] ^I [351] ^E [98] ^I
			Dir	[44] ^B [235] ^B
	Con and Agg	Inf	Hyb	[68] ^H
Ind			[288] ^B [287] ^B [219] ^B	
Tim, Loc and Sem	Occ, Ras and Cat	Inf	Dir	[239] ^B [6] ^B
	Dis, Ras and Cat	Inf	Dir	[79] ^P
			Ind	[56] ^P
	Dis, Ras and Agg	Inf	Dir	[349] ^N
			Gen	[170] ^H
		Dir	[248] ^P [143] ^P [121] ^P	