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INTEGRATING EXPERT TRUSTWORTHINESS INTO DIGITAL TWIN MODELS EXTRACTED FROM EXPERT KNOWLEDGE AND INTERNET OF THINGS DATA: A CASE STUDY IN RELIABILITY

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ABSTRACT

The extraction of Digital Twin models from both expert knowledge and Internet of Things data remains an underexplored area, with existing approaches typically being highly customized. Expert knowledge, provided by human experts, is influenced by individual experience, contextual understanding and domain-specific knowledge, leading to varying levels of uncertainty and trustworthiness. In this paper, we address the identified research gap by extending our previous work and introducing a novel approach that models and integrates expert trustworthiness into the extraction of what we term data-knowledge fused Digital Twin models. Key features of the approach are: quantifications of expert trustworthiness and algorithms for selecting and integrating knowledge into model extractions based on trustworthiness. We demonstrate our approach for quantifying and incorporating trustworthiness levels in a reliability modeling case study.

1 INTRODUCTION

Digital Twins (DTs) are increasingly adopted in both research and industry for their ability to simulate, analyze, and optimize complex systems (Vogel-Heuser et al. 2021). DTs are being applied across various domains, including aerospace, manufacturing, logistics and smart cities (Fuller et al. 2020). Data-driven model extraction approaches for DTs are gaining popularity, aiming to automate the creation and refinement of DTs using (real-time) Internet of Things (IoT) data (Friederich et al. 2022; Fuller et al. 2020). However, data-driven models can miss information and lack the contextual and experiential insights that domain experts provide, insights that are essential for accurate interpretation and decision-making (Jungmann and Lazarova-Molnar 2024b). Consequently, a systematic and seamless fusion of IoT data and expert knowledge for data-knowledge DT (DK-DT) model extractions leads to better-informed DT models.

Nonetheless, integrating expert knowledge presents its own set of challenges. Since expert knowledge statements (EKSs) originate from experts with varying levels of knowledge, experience and judgement, EKSs may contain ambiguity, incompleteness, errors or false assumptions. As a result, EKSs exhibit conflicts and divergences (Brugnach et al. 2008; Dewulf et al. 2005; Chowdhary 2020). These inaccuracies can undermine the quality and performance of DK-DT models. Therefore, EKSs must be validated, selected and weighted prior to integration. However, validating EKSs is difficult in the absence of objective ground truth. To address this, expert trustworthiness can serve as a proxy for estimating the potential accuracy of EKSs. By quantifying trustworthiness and applying a structured selection strategy, we can determine which EKSs to integrate to what extent, thereby improving the quality of DK-DT models.

Systematic and seamless approaches for DK-DT model extractions remain scarce in literature, presenting a significant research gap (Jungmann and Lazarova-Molnar 2024b). Notably, no existing work addresses DK-DT model extractions while integrating expert trustworthiness. To address this gap, we investigate the following research questions: 1) How can expert trustworthiness be modeled and quantified?; 2) How can expert trustworthiness be utilized to select EKSs for integration?; and 3) How can expert trustworthiness be integrated to extract better-informed DK-DT models?

To address the identified research gap and the proposed research questions, we present a novel approach that includes: (1) an approach to model expert trustworthiness, (2) an EKSs formalization and selection strategy for choosing among conflicting and complementary EKSs, and (3) extraction algorithms for generating Fuzzy Petri net-based DK-DT models considering expert trustworthiness and EKSs uncertainty.

The remainder of this paper is organized as follows. Section 2 provides background and related work on Digital Twins and expert trustworthiness modeling. In Section 3, we introduce our proposed approach, detailing the modeling of trustworthiness scores, the EKSs formalization, the EKSs selection strategy, and the model extraction algorithms. In Section 4, we demonstrate, validate and discuss our approach in a case study focused on reliability modeling. We conclude our paper in Section 5.

2 BACKGROUND AND RELATED WORK

In this section, we provide background and related work on DTs and uncertainty stemming from experts and EKSs. Furthermore, we conduct a literature review on trustworthiness in the context of DTs and experts.

2.1 Digital Twins and Corresponding Model Extraction Approaches

DTs gained attention in academia and industry in recent years (VanDerHorn and Mahadevan 2021) with various approaches. However, a unified framework or definition is still not available (Liu et al. 2023). We define a DT as a digital representative of a physical entity connected over a bi-directional information exchange, based on the definition by VanDerHorn and Mahadevan (2021). As distinction, related concepts of Digital Model and Digital Shadow do not feature a bi-directional communication (Kritzinger et al. 2018).

DTs have the potential to monitor, simulate, analyze and optimize a system of interest (Liu et al. 2023; Vogel-Heuser et al. 2021), enabling increases of reliability, efficiency, services, security and reliability as well as reductions of risks and costs for the system of interest (VanDerHorn and Mahadevan 2021). Based on their broad capabilities and potentials, DTs are applied in various domains such as aeronautics, healthcare, smart cities or manufacturing (Fuller et al. 2020; Liu et al. 2023).

DT models can be generated with multiple techniques, divided in three categories: 1) *knowledge-driven,* based on manual modeling efforts from experts; 2) *data-driven,* based on automated model extraction from IoT data; and 3) *hybrid*, based on model extraction from a fusion of both IoT data and expert knowledge (Wunderlich et al. 2021), which we refer to as *data-knowledge fused DT (DK-DT) model extraction*.

Knowledge-driven, data-driven and DK-DT model extraction approaches offer distinct advantages and face specific challenges (Jungmann and Lazarova-Molnar 2024b). The knowledge-driven approaches, for instance, often struggle with adaptability to frequent changes in the system (Friederich et al. 2022). In contrast, data-driven approaches may fail to capture critical patterns when data is sparse. To mitigate these challenges both approaches can be combined in a DK-DT extraction. With this, IoT data, which can miss relevant information, can be compensated through expert knowledge that includes context and experience. This can lead to better-informed DT models. However, data-knowledge fused approaches are highly complex and still an open problem (Jungmann and Lazarova-Molnar 2024a, 2024b).

In (Jungmann and Lazarova-Molnar 2024a, 2025), we started to address this gap by introducing novel approaches to extract DK-DT Petri net and Fuzzy Petri net models that also extract and integrate uncertainty from natural language EKSs. Here, we extend the latest approach to consider experts' trustworthiness.

2.2 Uncertainty Stemming from Experts and Expert Knowledge

Expert knowledge holds valuable information and is an important information source for complex systems (Brugnach et al. 2008; Dewulf et al. 2005). However, EKSs in natural language are diverge, complex, ambiguous (Chowdhary 2020) and contain uncertainty (Liu et al. 2017). Uncertainty can stem directly from EKSs or indirectly from expert (meta-) information (Jungmann and Lazarova-Molnar 2025) and is defined as divergence from absolute determinism (Janssen et al. 2010). Uncertainty is caused, e.g., as EKSs are stated by experts possessing individual levels of contexts, judgements, experience and decisions (Brugnach et al. 2008). In our previous work, we extracted uncertainty directly from EKSs, focused on the epistemic and especially ambiguous natural language aspects of uncertainty (Jungmann and Lazarova-Molnar 2025). Here, we focus on quantifying and modeling uncertainty beyond EKSs, stemming from (meta-) information about experts. We conceptualize this form of uncertainty as expert trustworthiness. In this paper, we define uncertainty due to ambiguity in EKSs as probability of belief that EKS happens as described, stated subjectively by the expert, and trustworthiness as the probability that the expert states correct EKS, which is more factual (Ohanian 1990; Liu et al. 2017). In the following, we conduct a literature review, first on trustworthiness in connection with DTs, and second about concepts of measuring expert trustworthiness.

2.2.1 Trustworthiness within the Digital Twin Domain

First, we analyzed relevant literature that addresses trustworthiness in the domain of DTs. Most studies focus on how to make DT models trustworthy to humans, as humans can have mistrust in the technology of DTs (Trauer et al. 2022). Examples for this are, e.g., literature focusing on credibility assessments for DTs by Shao et al. (2023), blockchain trust mechanisms by Sasikumar et al. (2023) or trust models utilizing DTs by John and John (2024). While explicit studies focusing on expert trustworthiness for DTs are limited, literature implicitly implies that system trust depends on the trustworthiness of each component and input (Shao et al. 2023; Hendriks et al. 2015), which would include the input of experts. Since we focus on the extraction of DK-DT models, we focus on the level of source expert trustworthiness to validate and select accurate EKSs as input for creating high-quality DK-DTs. However, we were unable to discover studies that consider trustworthiness of experts for the systematic integration of expert knowledge in the extraction of DK-DT models. We address this identified research gap with our approach to create better-informed models by utilizing the presumed accuracy of EKSs for their selection and integration into DK-DT models.

2.2.2 Trustworthiness of Experts: A Literature Review

Next, we review literature outside the DT domain. Most existing research focuses on how experts write and interact in online forums, reviews or debates, yet measuring trust remains inherently challenging (Besley et al. 2021). Literature about expert trustworthiness can be broadly categorized into two areas: 1) automated fact-checking; and 2) empirical, qualitative and theoretical source trustworthiness (Primiero et al. 2025). Given the limitations of fact-checking with sparse or abundant data (Primiero et al. 2025), we focus on source trustworthiness, which is more relevant for expert-scarce environments like manufacturing. This research often explores how laypeople perceive experts, using concepts like trustworthiness (Besley et al. 2021; Hendriks et al. 2015) and credibility (Fiske and Dupree 2014), though definitions vary. As some authors treat credibility as a component of trustworthiness (Cope 2014), we adopt trustworthiness as the overarching concept. We identify two main approaches for assessing trustworthiness: characteristic-based, relying on observable expert attributes; and situational, which evaluates trustworthiness dynamically.

In the following, we present literature that we classify under the category of characteristic trustworthiness. These studies primarily explore factors influencing the perceived trustworthiness of experts, mostly by laypeople. However, the body of literature identifying such factors remains relatively limited (Mihelj et al. 2022). Key contributions include works by Besley et al. (2021), Fiske and Dupree (2014), Hendriks et al. (2015) and Jarreau et al. (2019), who identify a range of influencing factors such as expertise, competence, warmth, integrity, good intentions, and adherence to scientific standards. Hendriks et al. (2015), further, propose the Muenster Epistemic Trustworthiness Inventory (METI) to assess epistemic trustworthiness of experts in laypeople. METI defines three categories of influence factors: expertise (competence), integrity (scientific standard compliance) and benevolence (good intentions). Besley et al. (2021) propose an extension to METI by introducing a fourth factor: openness to other opinions. Additional factors influencing trustworthiness are discussed by Gustafson and Rice (2019) and König and Jucks (2019), who highlight the role of language choice, communication channels, scientific consensus, controversy, and framing of uncertainty, particularly in complex domains such as climate science. Anderson et al. (2012) and Nisbet et al. (2002) note influence factors regarding media use and trust in experts and science.

In the following, we present literature categorized under situational trustworthiness, which addresses context-dependent evaluations of expert trustworthiness. Primiero et al. (2025) propose a computational model for dynamically ranking trustworthiness in settings where fact-checking is difficult. Mayweg-Paus and Jucks (2018) examine how written one-sided versus two-sided expert discussions influence university students' trust perceptions. Mihelj et al. (2022) explore public perception and its influence on trust formation and media usage during crisis such as COVID-19, focusing on low scientific trust in east Europe.

For this paper, we omit qualitative social studies and focus on quantitative approaches of expert trustworthiness as we aim to model a quantitative trustworthiness score. As our research targets professional environments (e.g., companies) and excludes lay audiences, we omit literature on crisis contexts, public communication, and factors such as warmth, language, media use, and openness to other views. We also exclude studies requiring broader contextual knowledge beyond limited expert settings. Thus, we focus the modeling of trustworthiness on literature that aligns with this setting and adapt it accordingly. Section 3.1 details how we integrate these insights into DK-DT models for trustworthiness assessments.

3 INTEGRATING EXPERT TRUSTWORTHINESS INTO DIGITAL TWIN MODELS EXTRACTED FROM EXPERT KNOWLEDGE AND INTERNET OF THINGS DATA

In this paper, we extend our previous approach (Jungmann and Lazarova-Molnar 2025) by introducing a novel semi-automatic approach that incorporates expert trustworthiness into the extraction of DK-DT models. In our approach, we first contribute algorithms that automatically model expert trustworthiness scores. Next, we introduce manual techniques and a selection strategy to formalize and select EKSs. Further, our algorithms automatically integrate and weigh the formalized EKSs based on their associated trustworthiness within the data-driven extraction of Fuzzy Petri nets as DK-DT models.

3.1 Modeling the Trustworthiness Score of Experts

We propose a novel dual-source expert trustworthiness score ($Trust(E_i)$) that is applicable in situations, where no fact-checking or validation via IoT data is possible. For example, if an EKS describes a fault that has not yet occurred and lacks sensor or maintenance log data. Equation (1) shows the calculation of $Trust(E_i)$ for expert E_i. Based on our exclusion criteria, we selected one quantification approach each from the characteristic and situational trustworthiness categories that we identified from literature. Both selected approaches form the basis of the $Trust(E_i)$ score. The dual-source approach enhances the robustness and informativeness of the proposed $Trust(E_i)$ by integrating two independent data types. The characteristic trustworthiness score ($CharacteristicTrust(E_i)$) is based on relatively static attributes such as *Expertise*, *Integrity*, and *Benevolence*, reflecting epistemic trustworthiness. The situational trustworthiness score ($SituationalTrust_r(E_i[\Phi_j])$) is derived from expert behavior and written EKSs. The $SituationalTrust_r(E_i[\Phi_j])$ is more dynamic, as behaviors in every discussion round r influence the trustworthiness of each expert. We weigh $SituationalTrust_r(E_i[\Phi_j])$ and $CharacteristicTrust(E_i)$ equally. To model $Trust(E_i)$, we assume that all required information for calculating both $CharacteristicTrust(E_i)$ and $SituationalTrust_r(E_i[\Phi_j])$ are available for expert E_i and opinion Φ_j. We also assume that experts can access the stated EKSs from other experts to, e.g., read or cite them and that we know which expert has stated and read which EKSs. In the following, we detail the modeling of $CharacteristicTrust(E_i)$ and $SituationalTrust_r(E_i[\Phi_j])$.

$$Trust(E_i) = 0.5 * CharacteristicTrust(E_i) + 0.5 * SituationalTrust_r(E_i[\Phi_j]) \quad (1)$$

3.1.1 Modeling the Characteristic Trustworthiness Score

We calculate the $CharacteristicTrust(E_i)$ by utilizing and modifying METI introduced by Hendriks et al. (2015). The main parameters of METI are *Expertise, Integrity* and *Benevolence*, each influenced by multiple sub-parameters. To only integrate sub-parameters in $CharacteristicTrust(E_i)$ with a high influence on trustworthiness, we select only sub-parameters that are assigned an influence value of greater 0.8 from Hendriks et al. (2015). In Table 1, we list the selected seven sub-parameters that match the influence value.

With this, sub-parameters such as helpful, fair and unselfish are excluded as they have a lower influence value and are assumed to be baseline expectations in professional environments. As we assume that the selected sub-parameters can be mapped from expert (meta-) information or stated by supervisors or peers in a professional environment such as a company, we, additionally, map them to our assumed examples where the information influencing the respective sub-parameter can be derived from. We show this mapping in Table 1. From the mapping, *Qualification* can be, e.g., derived from the job title of the expert. Sub-parameters under *Expertise* are more objectively measurable, e.g., *Education* or *Experience*, while those under *Integrity* and *Benevolence* are softer and behavior-related. We acknowledge that each human perceives other humans differently and judges subjectively. However, we assume for this work that in professional environments supervisors and peers assess as honestly and unbiasedly as possible.

Table 1: METI (sub-) parameters selected for the characteristic trustworthiness score.

Expertise	***Integrity***	***Benevolence***
Education – highest education	*Honesty* – supervisor/peer rating	*Moral* – supervisor/peer rating
Experience – years of affiliation		*Ethical* – supervisor/peer rating
Qualification – job title		
Competence – supervisor/peer rating		

METI is originally a three-dimensional scale. To model *CharacteristicTrust*(E_i) as a score and to ensure equal weighing of both scores contained in *Trust*(E_i), we further modify METI and compute *CharacteristicTrust*(E_i) as shown in (2). The parameters *Expertise*, *Integrity* and *Benevolence* are each calculated based on the sub-parameters in Table 1 and weighed equally to achieve a score between [0,1]. For this, the sub-parameter values are normalized relative to the expert group under consideration. For example, for *Education*, the expert with the lowest level of education is assigned a value of 0 and the expert with the highest level a value of 1. We assume that the calculation of *CharacteristicTrust*(E_i) is independent of the discussed topic, as experts state EKSs about areas that match to their expertise.

$$CharacteristicTrust(E_i) = \frac{\left(\frac{Education+Experience+Qualification+Competence}{4}\right)+(Honesty)+\left(\frac{Moral+Ethical}{2}\right)}{3} \tag{2}$$

3.1.2 Modeling the Situational Trustworthiness Score

We base our *SituationalTrust*$_r$($E_i[\Phi_j]$) on the work of Primiero et al. (2025) and their revisited computational trustworthiness ranking $t_k^{\#}$. However, we exclude their further revision t_k^{+}, where they include fact-checking, as it is treated as an oracle without a defined computational method and we also focus on areas where fact-checking is not suitable. We adapted $t_k^{\#}$ slightly to match our approach of *SituationalTrust*$_r$($E_i[\Phi_j]$) within a professional environment and adapted the notation e.g., to experts instead of agents. The calculation of *SituationalTrust*$_r$($E_i[\Phi_j]$) is presented in (3). To calculate this score, we first calculate the three dimensions: Reputation (*Reputation*$_r$($E_i[\Phi_j]$)), Popularity (*Popularity*$_r$($E_i[\Phi_j]$)) and Knowledgeability (*Knowledgeability*$_r$($E_i[\Phi_j]$)), which are each quantified scores that are calculated as displayed in (4) – (6). The dimensions are each weighed by a parameter p_k. E_i denotes expert i and Φ_j indicates topic or opinion j, where $E_i[\Phi_j]$ indicates E_i concerning Φ_j. As a prerequisite for *SituationalTrust*$_r$($E_i[\Phi_j]$), Φ_j are stated in several rounds r. Thus, results can differ depending on the round.

$$\begin{aligned} SituationalTrust_r(E_i[\Phi_j]) = {} & p_1 * Reputation_r(E_i[\Phi_j]) + p_2 * Popularity_r(E_i[\Phi_j]) \\ & + p_3 * Knowledgeability_r(E_i[\Phi_j]) \end{aligned} \tag{3}$$

$$Reputation_r(E_i[\Phi_j]) = \frac{|\,positive\ citations\,| + 1}{|\,positive\ citations\,| + |\,negative\ citations\,| + 2} \tag{4}$$

$$Popularity_r(E_i[\Phi_j]) = mean\left(\frac{|\,number\ of\ states,\ where\ written\ \Phi_j\ by\ E_i\ is\ read\ by\ another\ expert\,|}{|\,number\ of\ experts - 1\,|}\right) \tag{5}$$

$$Knowledgeability_r(E_i[\Phi_j]) = \frac{|\,number\ of\ states,\ \ where\ \Phi_j\ is\ read\ by\ E_i\ at\ r\,| + 1}{|\,number\ of\ states,\ \ where\ \Phi_j\ is\ written\ up\ to\ r\,| + 2} \tag{6}$$

In (4) both positive and negative citations are distinct from self-citations to receive a more unbiased result. Positive citations are the number of states, where Φ_j is written and sequentially trusted and, thus, accepted. Negative citations are the number of states, where Φ_j is distrusted and, thus, rejected by an expert. In (5), a mean is calculated for all messages stated by E_i, averaging how often each Φ_j is read by all experts except E_i divided by number of experts -1. We are aware that Popularity can result in values above 1, if Φ_j are read multiple times by different experts. As our *CharacteristicTrust*(E_i) delivers a result between [0,1] and we weigh both *CharacteristicTrust*(E_i) and *SituationalTrust*$_r$($E_i[\Phi_j]$) with an even influence, we aim to also have each characteristic result between [0,1]. Thus, we assume that opinions are only rarely read multiple times by experts. In Primiero et al. (2025), Knowledgeability is calculated with the denominator number of experts writing Φ_j until r-1 added with 2. As this leads to similar problems as with Popularity, if a small group of experts reads a high number of Φ_j, we adapted the denominator according to (6).

3.2 Formalization of Expert Knowledge Statements and Statement Selection Strategy

While much of the existing literature on DTs focuses on the manufacturing domain, reliability assessment remains a critical area within this field (Friederich and Lazarova-Molnar 2024). Since failures are costly and often undetectable via IoT data alone, we tailor our EKSs formalization to reliability-related information, specifically faults and event sequences. Faults act as triggers for failures and event sequences describe parts of the process flow. To formalize vague natural language statements, we utilize Weighted Fuzzy Production Rules (WFPRs) which effectively capture ambiguity in expert knowledge (Liu et al. 2017). WFPRs contain the parameters certainty factor μ, weight w and threshold λ (Liu et al. 2017). Here, we adapt w to reflect our expert trustworthiness score as weight w. WFPRs formalize EKSs with a structure of "IF *antecedent* THEN *consequent*". Both *antecedent* and *consequent* can consist of AND/OR compositions allowing multiple propositions (Liu et al. 2017). Further, we add an IN for stating the affected component and a THEN for event sequences. Our WFPR formalization is summarized in Table 2.

Table 2: WFPR formalization for EKSs integrating uncertainty and trustworthiness of experts.

Reliability Inform.	Cluster	WFPR Formalization Approach	Parameters
fault	involved component	IF + *condition(s)* + THEN + *state(s)* + IN + *component(s)*	(μ; w; λ)
event sequence	first consequent	IF + *event(s)* + THEN + *event(s)* + THEN + *event(s)*	(μ; w; λ)

To capture uncertainty, we calculate the certainty factor μ from language modifiers in natural language, following (Jungmann and Lazarova-Molnar 2025). To assign the weight w to each WFPR, we assume that *Trust*(E_i) can be directly correlated with EKSs stated by the expert E_i. We consider only those WFPRs where $w \geq \lambda$ to cluster the formalized WFPRs based on the criteria in Table 2. The clustering guides our selection strategy for the DK-DT integration. If two WFPRs in the same cluster are highly similar, e.g., describe the same sensor, but are contradictory, we retain the WFPR with the higher w and ignore the other(s). If the similarity of two WFPRs in the same cluster is low, we merge the antecedents using an OR composition, resulting in a XOR-split of transitions in the extracted DT model.

3.3 Extraction of Data-Knowledge Fuzzy Petri Nets Containing the Trustworthiness of Experts

Various modeling formalisms such as Petri nets, Fault Trees and Markov Chains can be used to describe DT models. We adopt Petri nets due to their compatibility with process mining from IoT data and their widespread use to model manufacturing systems (Friederich et al. 2022) within discrete-event simulations. We, further, use Fuzzy Petri nets (FPNs) for their ability to capture reasoning and knowledge with included uncertainty, imprecision, vagueness and fuzziness (Liu et al. 2017).

To integrate trustworthiness as an indicator of EKSs' presumable correctness, we require a weight assignment. As Weighted FPNs assign weights to places, we redefined the weights contained in WFPRs.

Following, we utilize *w* as firing weights of competing immediate transitions (Bause and Kritzinger 2002), as they match to different EKSs information joined with XOR-splits. Thus, trustworthiness, which more factually determines to which probability experts give EKS correctly, influences the firing weights and, thus, which enabled transition with activated guard function fires. The certainty factor, further, indicates the degree of belief that EKS happens as described, subjectively from the expert.

To extract FPNs enriched with trustworthiness, we extend our previous algorithms for fault and event sequence extractions using the a posteriori strategy, which directly derives information from EKSs. This approach is more broadly applicable than the a priori strategy, especially when IoT or synthetic data is unavailable (Jungmann and Lazarova-Molnar 2025, 2024a). We refer to the algorithm that extracts guard functions from EKS information on faults and creates XOR-splits for their assigned transitions based on our EKSs selection strategy as TRUST-FUZZY-POST-FA. We refer to the algorithm that extracts FPN places from event sequences as TRUST-FUZZY-POST-SEQ. Both algorithms are based and extend on the data-driven python libraries *ddra* (Friederich and Lazarova-Molnar 2022; Friederich 2023) and *pyspn* (Friederich and Lazarova-Molnar 2023). We show pseudocode extracts for both algorithms in Figure 1, illustrating how certainty factors and expert trustworthiness are integrated into DK-DT model extractions.

Algorithm 1: TRUST-FUZZY-POST-FA.

```
c = condition; t = transition; s = statement;
extract Fuzzy Petri net in data-driven manner;
for e in list of experts do
    calculate Trust(e) & assign to associated
      WFPR as weight w;
end
cluster WFPRs & select WFPRs for integration;
for s in IF-THEN-IN WFPR list do
    calculate μ from related natural language
      EKS & assign to s;
    extract c between "IF" and "THEN" of s;
    add immediate t for s & connect t to places;
    assign c as guard function, μ as certainty
      factor & w as firing weight to t;
end
```

Algorithm 2: TRUST-FUZZY-POST-SEQ.

```
ps = places; t = transition; s = statement;
extract Fuzzy Petri net in data-driven manner;
for e in list of experts do
    calculate Trust(e) & assign to WFPR as w;
end
cluster WFPRs & select WFPRs for integration;
for s in IF-THEN-THEN WFPR list do
    calculate μ from related natural language
      EKS & assign to s;
    extract first-t between "IF" and "THEN";
    extract second-t between "THEN"s;
    extract third-t after second "THEN";
    add timed t for second-t;
    calculate μ, w & assign to t;
    add two ps; connect ps to t, first-t & third-t;
end
```

Figure 1: Algorithms for extracting DK-DT FPNs, integrating uncertainty and trustworthiness.

4 CASE STUDY: INTEGRATING EXPERT TRUSTWORTHINESS IN THE EXTRACTION OF RELIABILITY-CENTERED DIGITAL TWIN MODELS IN MANUFACTURING

In this section, we present a proof-of-concept (PoC) case study to demonstrate our approach for integrating expert trustworthiness into the extraction of DK-DT models. As part of this integration, we determine the influence of each expert's related EKSs on the extracted DK-DT model. We begin by describing the case study setup, which we focus on the domain of manufacturing systems' reliability assessment.

4.1 Setup of the Case Study

This case study builds on our previous work (Jungmann and Lazarova-Molnar 2024a, 2025). The ground-truth model consists of two independent machines, Machine1 and Machine2, that process material. Machine2 receives material by an Automated Guided Vehicle (AGV). This ground-truth model is used to generate (synthetic) IoT data such as event logs and state logs. We, further, define a set of experts and corresponding EKSs that provide reliability-related insights about the system. Using both information sources, we rediscover a DK-DT model as FPN. The case study proceeds in five steps: 1) Creation of experts and EKSs; 2) Extraction of expert trustworthiness scores; 3) Formalization of EKSs into WFPRs, incorporating uncertainty and trustworthiness and determining WFPRs' selection into the model extraction; 4) Extraction of FPNs from both WFPRs and IoT data; and 5) Validation and discussion of our approach.

4.2 Step 1: Creation of Experts and their Provided Expert Knowledge Statements

In the absence of a real-world expert team, we define three expert profiles (E_1-E_3), each with distinct backgrounds, behaviors and experience levels. A summary of these profiles is provided in Table 3. We assume that the three designed experts provide their EKSs over three rounds, with a four-week interval in between. During these periods, experts can read, write or cite EKSs until the round concludes. Table 4 presents an excerpt of the EKSs generated by each expert across the rounds.

Table 3: Expert profiles of E_1 – E_3.

Expert 1 (E_1)	Expert 2 (E_2)	Expert 3 (E_3)
E_1 is in the second year of training. E_1 joined the company directly after school 1.5 years ago as a trainee with a three-year training plan. E_1 learns fast and works honestly, morally and ethically.	E_2 has gained a master's degree of engineering. E_2 is the head of the department with 20 years of company affiliation. However, E_2 uses the given power to maintain their position.	E_3 is an engineer specialized on machine failures. They have a 4-year company affiliation and 15 years of experience. Experts turn to E_3 if they have questions valuing their honest and moral answers.

Table 4: Extract of EKSs stated from experts E_1 – E_3 in three rounds.

	Round 1	Round 2	Round 3
E_1	It is very likely that an error in Machine1 occurs, when a noise of probably 90 decibel happens after Machine1 starts up.	Machine2 has a very delicate folding mechanism. If especially material5 arrives a bit twisted it is very likely the folding arms tilt and Machine2 fails.	I have to correct myself. I am now certain, that the error in Machine1 occurs, when the pressure jumps above 120 Pascal.
E_2	I am pretty sure that the AGV fails if the battery is below 25%, as the system accidentally shuts down when only limited energy is available.	If the stamp of Machine2 is used longer than 16 days, it is likely that Machine2 produces intermediate products with an error.	The AGV gets loaded certainly in the step load_manual after the step new_order and before the AGV can start to transport the material.
E_3	The chances are about even that the AGV fails during transport after the step line2_direction and the certain step manual_loading, if screw1 is untight.	If material arrives with a higher core temperature than 60 degree, it is not unlikely that Machine2 will fail within the next hour.	If Machine1 makes a sharp noise about 70 decibels the chances are about even that Machine1 will fail.

4.3 Step 2: Extraction of the Expert Trustworthiness Scores

Our two algorithms in Figure 1 automatically compute the trustworthiness score $Trust(E_i)$ based on expert (meta-) information. First, the algorithms calculate the characteristic trustworthiness score of the experts as shown in Section 3.1.1. To generate fictitious expert (meta-) information, we assign values to the sub-parameters in the formula for calculating $CharacteristicTrust(E_i)$ based on the expert profiles in Table 3, along with their fictitious positions, backgrounds and experience levels in a relative manner as described in Section 3.1.1. The resulting characteristic trustworthiness score for each expert is presented in Table 5.

Second, the algorithms calculate the situational trustworthiness score $SituationalTrust_r(E_i[\Phi_j])$ of each expert, as described in Section 3.1.2. For this limited PoC, we assume that we can summarize and simplify the EKSs of the manufacturing system of interest to one topic with different opinions to not separate topics according to components or fault types. For each expert and round, we collect various fictitious (meta-) information respective to Φ_j, such as read, write, positive and negative citation actions. We present the collected data in Table 6. From this information, the algorithms calculate $Reputation_r(E_i[\Phi_j])$, $Knowledgeability_r(E_i[\Phi_j])$, $Popularity_r(E_i[\Phi_j])$ and $SituationalTrust_r(E_i[\Phi_j])$ for each expert and round, displayed in Table 6. We assume all dimensions as equally important and, therefore, assign p_k for each as $0.\overline{3}$ in $SituationalTrust_r(E_i[\Phi_j])$. For Popularity we consider detailed read information of each of the written messages, where, e.g., message1 of E_1 is read two and message2 zero times by experts. For simplification, we calculate *Mean Reads Per Message* which captures the average of how many times each message written by E_i is read by experts except E_i. Further, we directly insert this mean as numerator in $Popularity_r(E_i[\Phi_j])$.

Finally, the algorithms calculate the dual-source trustworthiness score $Trust(E_i)$ as introduced in Section 3.1. We present the final $Trust(E_i)$ score only after the third round in Table 7 as in this case study the DK-DT FPN model is extracted once when the third round is finished.

Table 5: Calculation of the characteristic trustworthiness score *CharacteristicTrust(E_i)* for $E_1 - E_3$.

CharacteristicTrust(E_1)	***CharacteristicTrust(E_2)***	***CharacteristicTrust(E_3)***
$\frac{\left(\frac{0.3+0.2+0.5+0.8}{4}\right)+0.8+\left(\frac{1+1}{2}\right)}{3} = 0.75$	$\frac{\left(\frac{0.9+0.8+0.9+0.6}{4}\right)+0.85+\left(\frac{0.6+0.7}{2}\right)}{3} = 0.7667$	$\frac{\left(\frac{0.5+0.7+0.8+0.9}{4}\right)+0.9+\left(\frac{0.9+1}{2}\right)}{3} = 0.8583$

Table 6: Calculation of the situational trustworthiness score *SituationalTrust$_r$($E_i[\Phi_j]$)* for $E_1 - E_3$.

	E_1R_1	E_1R_2	E_1R_3	E_2R_1	E_2R_2	E_2R_3	E_3R_1	E_3R_2	E_3R_3
Read Messages	20	25	33	4	11	11	26	32	67
Written Messages	7	10	17	3	14	19	16	22	31
Positive Citations	1	3	8	0	2	6	2	12	15
Negative Citations	2	5	5	0	5	9	0	1	1
Mean Reads Per Message	1.2	1	2	1.6	1	1.4	0.8	2.4	0.8
Reputation$_r$($E_i[\Phi_j]$)	0.4	0.4	0.6	0.5	0.3333	0.4118	0.75	0.8667	0.8889
Knowledgeability$_r$($E_i[\Phi_j]$)	0.75	0.5417	0.4928	0.1786	0.25	0.1739	0.9643	0.6875	0.9855
Popularity$_r$ ($E_i[\Phi_j]$)	0.6	0.5	1	0.8	0.5	0.7	0.4	1.2	0.4
SituationalTrust$_r$($E_i[\Phi_j]$)	0.5833	0.4806	**0.6976**	0.4929	0.3611	**0.4286**	0.7048	0.9181	**0.7581**

Table 7: Calculation of the dual-source trustworthiness score *Trust(E_i)* for $E_1 - E_3$.

Trust(E_1)	***Trust(E_2)***	***Trust(E_3)***
0.5 * 0.6976 + 0.5 * 0.75 = **0.7238**	0.5 * 0.4286 + 0.5 * 0.7667 = **0.5976**	0.5 * 0.7581 + 0.5 * 0.8583 = **0.8082**

4.4 Step 3: Formalization of EKSs into WFPRs and Selection of which EKSs to Utilize

This step involves both manual and automated processes. First, we manually formalize the EKSs from Table 4 into WFPRs based on contained fault or event sequence information, following the structure in Table 2. Then our TRUST-FUZZY-POST-FA/-SEQ algorithms assign the previously calculated expert trustworthiness scores to each respective WFPRs as weight *w* and cluster the WFPRs. Using these clusters and weights, we manually apply our selection strategy. With this strategy, we eliminate E_1R_1 and keep E_3R_3, as E_3R_3 is assigned a higher *w* for the conflicting information in the same cluster. The same holds for the elimination of E_2R_3 in favor of E_3R_{1b}. Further, the algorithms calculate and assign the certainty factor μ for each WFPRs. For this PoC, the threshold λ is set to 0.5 as an experiment to exclude all EKSs related with a lower trustworthiness of the stating expert. A summary of these steps is provided in Table 8.

Table 8: Clustered, formalized and selected WFPRs with assigned parameters.

WFPR	**Cluster**	**WFPR Formalized EKS**	***μ***	***w***	***λ***
E_1R_1	Machine1	IF noise >= 90 THEN failure IN Machine1	0.85	0.7238	-
E_2R_1	AGV	IF battery < 25 THEN failure IN AGV	0.92	0.5976	0.5
E_3R_{1a}	AGV	IF screw1 == untight THEN failure IN AGV	0.745	0.8082	0.5
E_3R_{1b}	Manual	IF direct _line2 THEN manual_loading THEN agv_transport	0.745	0.8082	0.5
E_1R_2	Machine2	IF material5 == twisted THEN failure IN Machine2	0.85	0.7238	0.5
E_2R_2	Machine2	IF stampAge > 16 THEN failure IN Machine2	0.78	0.5976	0.5
E_3R_2	Machine2	IF materialTemp. >= 60 THEN failure IN Machine2	0.515	0.8082	0.5
E_1R_3	Machine1	IF pressure >= 120 THEN failure IN Machine1	0.995	0.7238	0.5
E_2R_3	Manual	IF new_order THEN load_manual THEN agv_transport	0.995	0.5976	-
E_3R_3	Machine1	IF noise >= 70 THEN failure in Machine1	0.495	0.8082	0.5

4.5 Step 4: Extraction of Data-Knowledge Fuzzy Petri Net Models Including Trustworthiness

We automatically extract the FPN using our TRUST-FUZZY-POST-FA/-SEQ algorithms. The resulting FPN is shown in Figure 2, redrawn for clarity. In Figure 2, expert knowledge integrations are highlighted using colored boxes. As our algorithms only integrate WFPRs that were chosen by our selection strategy, E_1R_1 and E_2R_3 are omitted for integration. From WFPRs, formalized for fault information, the TRUST-FUZZY-POST-FA algorithm derives transitions and assigns them each a guard function, certainty factor μ and transition firing weight *w*. For example, based on our selection strategy both E_3R_3 (noise fault) and

E_1R_3 (pressure fault) are integrated into the FPN each with an individual transition (fail_machine_1) connected over an XOR-split, as they describe distinct complementing failure behaviors. With the TRUST-FUZZY-POST-SEQ algorithm, E_3R_{1b} is integrated into the FPN by adding two new places and a manual_loading transition in between, as an alternative path to the one extracted from (synthetic) IoT data.

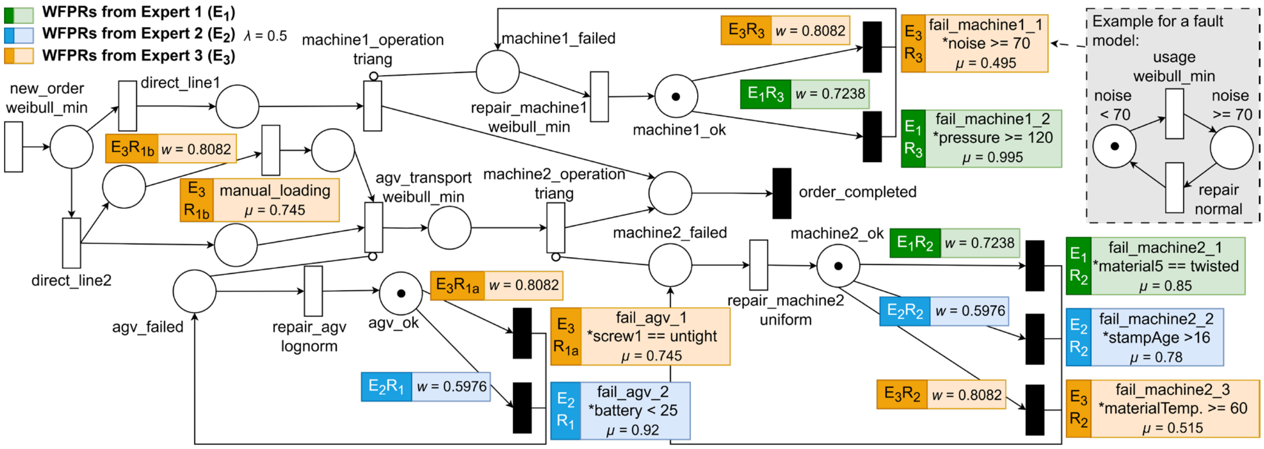

Figure 2: Extracted FPN containing guard functions, uncertainty and trustworthiness.

4.6 Step 5: Validation and Discussion

To validate the extracted DT model, we conducted a face validation to verify the transitions, places, guard functions, certainty factors and (firing) weights as trustworthiness scores, derived from both IoT data and EKSs. Our TRUST-FUZZY-POST-FA/-SEQ algorithms correctly inserted XOR-split transitions into the FPN for OR related fault WFPRs based on our EKS selection strategy. The algorithms also added places and transitions for event sequence WFPRs. Additionally, elements such as guard functions, μ, w and λ, extractable only through EKSs in this PoC, are correctly integrated to the transitions.

Beyond model validation, our approach supports informed decision-making for sensor deployment to track reliability-relevant data. For example, based on the extracted FPN (Figure 2), we identify the need for screw and battery sensors for the AGV, and noise and pressure sensors for Machine1. This demonstrates how expert knowledge not only enhances DT model extractions but also guides real-world system improvements, such as enabling automated fault detection. Once these missing sensors are installed, we can automatically extract probability distributions for both sensor values and the timing of fault occurrences. These probability distributions are essential for simulating the DT model for reliability assessment. An example of a Petri net fault model that captures probability distribution of a fault, specifically the noise in Machine1, as described by E_3R_3, is illustrated in the grey dotted box in Figure 2.

A key limitation of our PoC is that DT models are currently extracted only after all EKSs are collected. They are not dynamically updated based on evolving trustworthiness scores as new EKSs become available. We, additionally, identify three initial areas for improving our trustworthiness score calculation, which we aim to address in future work: 1) rankings from supervisors or peers are inherently subjective, which makes a comparison of characteristic trustworthiness scores difficult; 2) within the situational trustworthiness score, the dimension popularity can distort the result, e.g., when the supervisor reads every trainee statement; and 3) currently, trustworthiness scores are related to the system and are not utilized to assign separate scores for system components, which gets relevant if, e.g., experts are specialized. Addressing this would require more granular data, which may raise privacy concerns under data protection laws, e.g., the General Data Protection Regulation. However, we also focus on expert information that is (semi-) publicly available, as this information could be common knowledge within a company or stated from experts themselves publicly on social platforms such as their education, job title, affiliation and their opinions.

5 SUMMARY AND OUTLOOK

In this paper, we present a novel approach for integrating expert trustworthiness into the extraction of data-knowledge Digital Twin models. We introduce a dual-source expert trustworthiness score, a formalization approach incorporating expert trustworthiness and certainty factors, and a selection strategy for selecting expert knowledge statements. We proposed two algorithms to fuse data and expert knowledge input into data-knowledge Digital Twin models including expert trustworthiness and certainty factors. Incorporating expert trustworthiness enables a selection of conflicting and complementing expert knowledge and the weighed integration of this knowledge into Digital Twin models based on their assumed accuracy, making them more robust. Future work includes validation on real-world case studies, refining thresholds, improving update cycles of expert knowledge, resolving conflicting data and knowledge inputs, exploring anonymization and leveraging Large Language Models.

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