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Organizational, Sociological and Procedural Uncertainties in Statistical and Machine Learning: A Systematic Literature Review

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Abstract

Driven by the potential of digitalization, statistical learning and machine learning methods are commonly used for scheduling complex processes or forecasting in supply chain domains. However, trust in such methods is hampered by uncertainties in data quality, data exchange platforms, and data processing, affecting its traceability and reliability. Decision-relevant output provided by such methods is prone to trust issues in the data used for training, in the resulting model, and in the infrastructure in which the model is embedded. Considering the vulnerability of supply chains, wrong decisions have far-reaching consequences, raising the question of to what extent systems alone should be trusted for strategic, operational, and tactical decision-making. In this paper, we take a multidisciplinary perspective with the intention to analyze trust in statistical learning and machine learning methods from an organizational, sociological, and procedural perspective. The information base for this article is gathered through a systematic literature review. The central results of our research are a concept matrix comparing papers based on relevant criteria derived from literature and subsequent findings derived from this matrix. We encourage researchers in the fields of supply chain management, sociology, and statistics or machine learning to open up for interdisciplinary research and to build upon our findings.

Keywords

Trust; Uncertainty; Statistical Learning; Machine Learning; Supply Chain Management; Literature Review

1. Introduction

Supply chain actors are subject to vulnerability and interdependence of partners within a value network, in which trust becomes increasingly relevant [1]. In the era of digitalization and Industry 4.0, the omnipresent efforts of data collection and utilization provide companies with a decision basis for estimating the recent status and upcoming changes of asset conditions and processes [2]. As part of so-called decision support systems, companies use statistical learning and machine learning methods exemplarily for forecasting or classification [2]. Statistical learning and machine learning methods belong to the ubiquitous field 'artificial intelligence' (AI) [3]. Because most decision-makers in supply chain management are less experienced in statistics and computer science, ambiguity in their use is considerable [4]. Knowing when and why to trust such methods is mandatory to enable decision-makers to make resilient decisions under remaining uncertainty in the data and its further processing [4].

Our research deals with trust and uncertainty issues evoked by statistical learning and machine learning methods resulting from a lack of transparency about the interplay of the data, model, and the infrastructure in which it is embedded. However, considering only an organizational lens neglects a profound

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understanding of how and why uncertainties arise in statistical learning and machine learning methods at different levels (micro, meso, macro). Therefore, a complementary view from an organizational, sociological, and statistical or machine learning perspective (which we call a procedural perspective) is necessary. The research question of our article is: “To what extent do recent research activities investigate uncertainties from organizational, sociological, and procedural perspectives, considering the use of statistical learning and machine learning methods in the field of supply chains?”. Our paper consists of the following structure: In chapter 2 we introduce relevant criteria for each perspective as related background. In the third chapter, we present the methodology and specifics of our literature review. In chapter 4 we visualize the results of our literature review with a concept matrix. We condense our findings intra- and inter-perspectively. Chapter 5 concludes our key findings and gives an outlook for future research.

2. Criteria on Trust and Uncertainty in Statistical Learning and Machine Learning

The triad of organizational, sociological, and procedural perspectives allows us to take a sociotechnical view on trust in statistical learning and machine learning methods. For each perspective, we present the related background and derive appropriate criteria, which provide the deductive framework for the systematic literature review.

2.1 Organizational Perspective on Trust and Uncertainty in Statistical and Machine Learning

From an organizational perspective, contributions differ to the underlying coordination structure, which is either an inter-organizational (market, network) or an intra-organizational (hierarchy) perspective [5,6]. With the era of Industry 4.0 and associated digitalization efforts, trust becomes relevant to information systems in buyer-consumer relationships [7]. For supply chain management (SCM), inter-organizational trust plays an important role, especially if dependencies with partners or third-party intermediates are involved [1]. The literature on trust is manifold. Trust can take different forms [8] and is affected over time [9]. Trustworthiness as an antecedent of trust can be affected by the triad interplay of ability, benevolence, and integrity [10]. According to Zaheer et al. [11], trust relates to a single person (interpersonal trust) or to an organization (inter-organizational trust). Once established, trust within a network contributes to reduced coordination effort [5] relevant for deciding about make-or-buy [12]. Artificial intelligence is considered as an instrument enhancing the competencies of decision-makers, but the effort to calibrate such tools varies with the complexity of the planning scenario (e.g. supplier selection, layout planning, etc.) [4]. To prevent the use of statistical and machine learning leads to an increase in ex-post coordination effort, such as subsequent follow-up discussions between supply chain partners, an understanding of the upcoming uncertainties and the extent of trust in such methods is required, before applying those for (inter-)organizational purposes.

2.2 Sociological Perspectives on Trust and Uncertainty in Statistical and Machine Learning

In sociology, trust and uncertainty are complex and multidimensional concepts. Trust in AI refers to the confidence, belief, and trust that individuals (micro level), organizations (meso level), or societies (macro level) place in AI systems, algorithms, and technologies. It includes the expectation that AI systems will behave in a trustworthy and reliable manner, taking into account their impact on individuals, communities, and society as a whole. In other words, when AI systems are implemented in social environments, they assume social roles, engage in social practices, and form social ties [13]. Social action is, in general, complex and involves a high degree of uncertainty and lack of control [14]. Thus, from a sociological perspective, it is important to consider how AI systems penetrate and transform social institutions, redefining social life in the process [15]. In the 1980s and 1990s, AI was discussed in sociology as a system of science and knowledge that attempted to make machines capable of doing what humans can [13]. AI’s various applications are the subject of most recent studies [16–18]. One of the most debated issues in this context is whether AI threatens human (knowledge) workers or not. The goal of a sociological perspective is to understand how trust in AI is formed, maintained, or eroded, and how it affects social relationships, institutions, and power dynamics.

2.3 Procedural Perspectives on Trust and Uncertainty in Statistical and Machine Learning

Trust in AI models is necessary for their deployment in any application. In this paper, we consider statistical learning and machine learning methods which are an important subset of AI methods. Statistical learning and machine learning methods comprise classification and regression techniques that create models serving two purposes: prediction and interpretation. The focus of machine learning methods traditionally is predicting the target of interest for new data as accurately as possible. For statistical learning methods, the interpretability of the resulting models is of utmost importance as the aim is to understand the influence of the features on the target variable [19]. From a statistical learning and machine learning point of view, trust in a predictive model depends on its accuracy, its communication of statistical uncertainty, and its interpretability. Accuracy refers to the average quality of the model's predictions for new data. Knowing the accuracy of a model is essential for judging the credibility of predictions as well as any conclusions derived from the model [20]. Statistical uncertainty refers to the model's confidence in individual predictions and consists of epistemic uncertainty (model uncertainty) and aleatoric uncertainty (data uncertainty) [21]. Quantifying statistical uncertainty allows for assessing the believability of individual predictions as well as specifying ranges of plausible prediction values. The model's interpretability refers to the understandability of why a certain prediction is obtained for a certain input. While interpretability comes naturally for statistical learning methods, various tools for explaining complex black-box machine learning models have been proposed in the last decades [22].

3. Methodology: Systematic Literature Review

We follow the systematic literature review (SLR) proposed by vom Brocke et al. [23] to ensure a rigorous approach. Similar to [24], we transfer our findings into a concept matrix. Following [23], we define and review our scope, followed by the conceptualization of logic and the resulting literature research. The literature analysis and synthesis lean against the dimension proposed in the prior section (e.g. the criteria of each perspective). Based on the resulting concept matrix, we derive a research agenda for multidisciplinary research. Relating to [25], the focus of our SLR set on research outcomes with the goal of depicting central issues, organized conceptually, taking a neutral representation, and using general scholars with a representative, but not exhaustive coverage of literature.

Table 1 illustrates the process of our SLR. To ensure a high degree of coverage of literature, we use Scopus, Web of Science, and AISeL as preferred databases. Since Scopus allows the most complex constellation of keywords, we use it as the primary database and adapt the query to the possible functionalities of each database (such as limited wildcard operators, non-availability of near- or within-operators, etc.). We export the results of each database as a BibTex and merge them in the literature management program Citavi to remove duplicates. Then, we exclude non-available since we need access to data beyond the regular meta information (author, title, abstract, keywords) to ensure that the content is relevant to our research.

The literature review relates to queries conducted in June 2023. In the first iteration, we filter the paper by screening the title and abstract based on their contextual relevance, resulting in 48 papers. Subsequently, we select the papers based on a deep-dive analysis, in which we excluded papers that are out of our intended scope, leading to a remaining amount of 35 papers. We analyze and discuss our findings in the next chapter.

Table 1: Overview of the SLR

Database	**Scopus**	**Web of Science**	**AISeL**
Search String Composition	TITLE-ABS-KEY (("trust*" OR "quality uncertaint*" OR "uncertaint*") AND ("Machine Learning" OR "Data Mining" OR "Pattern Recognition" OR "Computational Intelligence" OR "Statistical Learning" OR "Statistical Modeling" OR "Predictive Modeling" OR "Supervised Learning" OR "Regression Analysis") AND ("Socio*" OR "Socia*" OR "ethics" OR (Human AND Interaction)) AND ("interorganization*" OR "interorganisation" OR "network") AND ("logistic*" OR "Supply Chain*" OR "product*" OR "maint*" OR "purchas*" OR "sales and distribution"))		
Notes to Search String	The search string above is the final query used for Scopus. The query deviates between WoS and AISeL due to functionality restrictions.		
Initial Results	345	46	36
Results: 1st Iteration	48		
Results: 2nd Iteration	35		

4. Findings and Discussion

Considering the publication year, 77% of the papers have been published within the last five years. An almost constant distribution over the years can be stated. This suggests that the research topic addressed in our paper retains a constant level of attention. In the next step, we analyze each perspective and underlying criteria (see section 2). Coming from different disciplines, we have chosen nine criteria for our review to provide a comprehensive assessment of our research topic. In addition, the nine criteria allow for a more in-depth assessment of different aspects, which can be particularly useful for a complex or multifaceted topic such as uncertainties in statistical learning and machine learning. Table 2 visualizes the findings through a concept matrix. For each perspective, we discuss the central findings, based on quantitative and qualitative material. Each of the selected paper addresses at least one criterion of each perspective.

4.1 Findings from an Organizational Perspective

From an organizational perspective, 71% of the papers deal with trust and trustworthiness. Relating to the coordination structure, 9% of the papers cannot be assigned to any [26–28]. Of the 32 papers, 25% address hierarchical, 6% market-based, and 65% network-based issues (including multiple assignments). While both market-based papers consider trust or trustworthiness, e.g. [29,30], it is only considered in 75% of the contributions assigned to hierarchy and in 65% of the ones relating to networks. 25% address topics related to the supply chain. All of them can be assigned to network-based content, e.g. [31–39]. However, only 33% of them mention trust or trustworthiness, e.g. [31,34,37], which are the only contributions covering content on all three criteria. This shows that there is scarce literature addressing trust-related issues in supply chain management using statistical learning and machine learning methods.

4.2 Findings from a Sociological Perspective

Facing the sociological perspective, about 85% of the papers are based on empirical research. Considering the engagement of AI in social practices, 34% of the papers address a macro-layer, 42% a meso-layer, whereas 22% consider a micro-layer (including multiple assignments). 8% of the paper cannot be assigned to any of them. Out of all 35 papers, there is no contribution elaborating on a sociological understanding of uncertainty. Analyzing the set of publications from a sociological perspective, it must be noted that the role of trust and uncertainty in social dynamics does not play a role in the literature review at this point in time. This is particularly evident in the lack of definitions of trust and uncertainty, although these concepts play a central role in the present papers. Thus, addressing societal concerns, ensuring responsible AI development and deployment, and promoting individual (micro-level), organizational (meso-level), and public (macro-level) participation in shaping AI policy and practice remains a gap in AI research.

4.3 Findings from a Procedural Perspective

Of the 35 publications presented in Table 2, 80% address predictive accuracy by discussing it on a conceptual level, e.g. [26,40,41], or by assessing the predictive performance of one or more models in their empirical study, e.g. [42–45]. 60% of the publications in Table 2 deal with the topic of statistical uncertainty. [27] propose a new approach for non-overly-optimistic uncertainty quantification. [46,47] account for uncertainty by providing confidence intervals instead of just point estimates. 69% of the publications in Table 2 broach the issue of interpretability. [32,48,49,33,46,34,47,30,50,39] create statistical models with the purpose of interpreting them in order to gain insight into the influence of features on the target of interest. [26,40,51,41,52] address the topic 'explainable AI' on a conceptual level. [28] provide an overview of methods for interpretable machine learning. [53] base the choice of learning method on the understandability of the resulting model for practitioners. 21% of the publications thematizing accuracy neither address uncertainty nor interpretability. Most of these are method comparison studies, e.g. [42,44,45,54]. 86% of the papers thematizing uncertainty and 75% of the papers thematizing interpretability also talk about accuracy, often because accuracy is an aspect commonly reported when elaborating on models in detail.

Table 2: Concept matrix
(H: Hierarchy, N: Network, M: Market; EM: Empirical; NE: Non-Empirical; MI: Mikro; ME; Meso; MA: Makro)

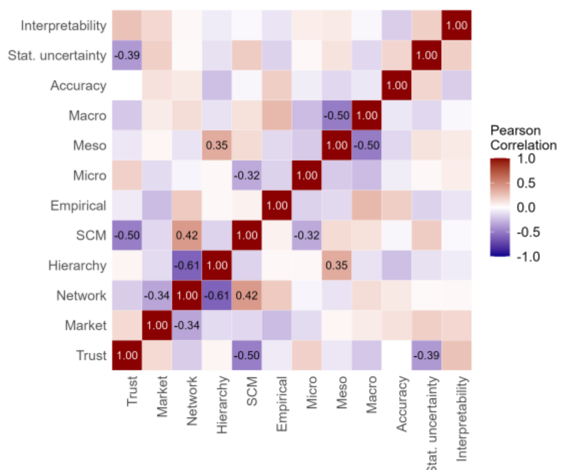
Sources	Publication Year	Perspective								
		Organizational			Sociological			Procedural		
		Trust or Trust-worthiness	Coordination Structure	SCM	Type of paper	Engagement of AI in social practices	Sociological understanding of uncertainty	Accuracy	Statistical uncertainty	Interpretability
[26]	**2019**	**X**			**NE**	**MI**		**X**	**X**	**X**
[27]	**2022**	**X**			**EM**			**X**	**X**	
[28]	**2019**	**X**			**EM**			**X**		**X**
[29]	**2020**	**X**	**M**		**NE**	**ME**		**X**	**X**	**X**
[30]	**2022**	**X**	**M**		**EM**	**MA**		**X**	**X**	**X**
[31]	**2021**	**X**	**N**	**X**	**EM**	**MA**		**X**		**X**
[32]	**2018**		**N**	**X**	**EM**	**MA**		**X**	**X**	**X**
[33]	**2014**		**N**	**X**	**EM**	**MA**			**X**	**X**
[34]	**2011**	**X**	**H, N**	**X**	**EM**	**ME**		**X**	**X**	**X**
[35]	**2017**		**N**	**X**	**EM**	**ME**		**X**	**X**	
[36]	**2018**		**N**	**X**	**EM**	**MA**		**X**		
[37]	**2019**	**X**	**N**	**X**	**EM**	**ME**		**X**	**X**	**X**
[38]	**2021**		**N**	**X**	**NE**	**ME**			**X**	
[39]	**2018**		**N**	**X**	**EM**	**ME**		**X**	**X**	**X**
[40]	**2020**	**X**	**N**		**EM**	**ME**		**X**		**X**
[41]	**2023**	**X**	**N**		**NE**	**MI**		**X**	**X**	**X**
[42]	**2023**	**X**	**H**		**EM**			**X**		
[43]	**2015**		**H**		**EM**	**MA**		**X**	**X**	
[44]	**2021**	**X**	**N**		**EM**	**MA**		**X**		
[45]	**2019**	**X**	**N**		**EM**	**ME**		**X**		
[46]	**2017**	**X**	**N**		**EM**	**MI**		**X**	**X**	**X**
[47]	**2017**	**X**	**H**		**EM**	**ME**		**X**	**X**	**X**
[48]	**2017**		**N**		**EM**	**ME**		**X**	**X**	**X**
[49]	**2020**	**X**	**N**		**EM**	**MA**			**X**	**X**
[50]	**2017**		**N**		**EM**	**MA**		**X**	**X**	**X**
[51]	**2022**	**X**	**H**		**NE**	**ME**				**X**
[52]	**2023**	**X**	**H**		**EM**	**ME**				**X**
[53]	**2018**	**X**	**N**		**EM**	**ME**		**X**	**X**	**X**
[54]	**2020**	**X**	**N**		**EM**	**MI**		**X**		
[55]	**2020**	**X**	**H**		**EM**	**MI, ME, MA**				**X**
[56]	**2023**	**X**	**N**		**EM**	**MI**				**X**
[57]	**2020**		**H**		**EM**	**MI, ME**		**X**	**X**	
[58]	**2021**	**X**	**N**		**EM**	**MI**		**X**	**X**	**X**
[59]	**2019**	**X**	**N**		**EM**	**MA**		**X**		
[60]	**2021**	**X**	**N**		**EM**	**MA**		**X**		**X**

4.4 Overfall findings

None of the publications in our analysis addresses all 9 criteria displayed in Table 2. Three publications address 8 criteria, nine publications address 7 criteria, eight publications address 6 criteria, twelve publications address 5 criteria, and three publications address 4 criteria. On average, the publications address 65% of the criteria stated in Table 2.

To analyze the intra- and interdisciplinary connections between the criteria stated in Table 2, we compute the Pearson correlation coefficients between all pairs of criteria using R [61]. We dummy-encoded the criteria with more than two categories and removed the constant criterion “sociological understanding of uncertainty” (for which the Pearson correlation is undefined). The Pearson correlation takes values from - 1 to 1. A negative correlation value indicates that only one (but not the other) encoded criterion is addressed in comparably many publications, whereas a positive correlation value indicates both or neither of the criteria being addressed in the same publication for comparably many papers. Table 3 illustrates the correlation matrix. To reduce the visualization to the most relevant results, we applied a threshold of ±0.30. Based on this, the associations of eight pairs of criteria are analyzed more closely in Table 3.

Table 3: Findings based on Pearson correlations and ±0.30 as threshold

Results	Analysis
	**<u>Organization only:</u>** 1. Network-like approaches correlate negatively with hierarchical approaches due to almost exclusive assignment (-0.61) 2. Market-like approaches correlate negatively with networks due to mutually exclusive assignment (-0.34) 3. Trust and SCM correlate negatively due to the high amount of trust-related literature outside the case of SCM (-0.50) 4. SCM and networks correlate positively due to the fact that inter-organizational networks are inherent in supply chains (+0.42) **<u>Sociology only:</u>** 5. Macro- and meso-layer correlate negatively due to the absence of intersecting or all-encompassing paper (-0.50) **<u>Organization and Statistic:</u>** 6. Statistical uncertainty and trust correlate negatively since statistical analyses incorporate statistical uncertainty but do not mention trust explicitly (-0.39) **<u>Organization and Sociology:</u>** 7. Hierarchical approaches correlate positively to meso-layer, since both terms address institutional facets (+0.35) 8. SCM correlates negatively to micro-level (-0.32) since the 8 papers about SCM are only focussing on network issues

5. Conclusion

The aim of this paper was to assess the extent to which the recent literature covers the triad interplay of organizational, sociological, and procedural perspectives in the context of trust in statistical and machine learning. To answer the question, we conducted a systematic literature review in which we assessed whether nine criteria introduced by us were addressed in the publications. Subsequently, we analyzed the results based on the Pearson correlations.

Our analysis has revealed several key insights and implications for both researchers and practitioners in the field. First, our findings suggest that the existing literature in supply chain management does indeed recognize the importance of the interplay between organizational, sociological, and procedural factors when it comes to trust in statistical learning and machine learning technologies. This recognition is crucial as it reflects a holistic understanding of trust dynamics in the context of modern supply chains, which increasingly rely on data-driven decision-making processes. Second, we have identified certain gaps in the current body of knowledge. We observed that none of the papers analyzed in our literature review addressed all criteria and that on average, the papers addressed 65% of the criteria. While there is a growing body of research that touches on these three perspectives individually, there is room for more comprehensive studies that explicitly explore how they interact and influence each other. Analyzing the associations between the criteria led us to insights such as that many statistical analyses incorporate uncertainty without mentioning explicitly the trust-building effects of these incorporations. Future research should aim to delve deeper into these interactions to provide a more nuanced understanding of trust dynamics in supply chain management. In addition, our analysis highlights the importance of considering the practical implications of these findings. Supply chain managers and decision-makers should be aware of the complex relationship between organizational culture, social factors, and procedural aspects when implementing statistical learning and machine learning technologies. Creating an environment that fosters trust requires not only investing in cutting-edge technology, but also fostering a culture of data literacy, transparency, and accountability.

Note that the criteria displayed in the concept matrix have been assessed independently. Thus, at the current stage, the overall findings make no claim of generalizability. A complementary analysis including inter-coder-reliability with more than one person assessing each perspective could give indications about the existence and extent of a subjectivity bias [62]. Building upon this, we encourage researchers to conduct more research from multidisciplinary perspectives with the intention to consider the interdependencies between all perspectives.

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