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Technical Readiness of Prescriptive Analytics Platforms: A Survey

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***Abstract*—Decision-making is the process of selecting a course of action from several alternatives on the basis of preferences, values and available information. As decisions become increasingly complex, the use of data for decision-making is on the rise. The growing popularity of data-driven decision-making has led to the launch of countless data analytics platforms and in particular prescriptive platforms for decision support. Prescriptive analytics is the highest form of data analytics, which aims to find the optimal action for a given situation. The main focus of this paper is to provide a deep insight into the state-of-the-art of existing prescriptive platforms. To this end, we survey the prescriptive research landscape in all domains and highlight which data, protocols, databases, and algorithms the respective platforms work with to provide reasonable actions. We further review the level of readiness in terms of the status of implementation and usability of the proposed action. In addition, we derive a framework for prescriptive platforms that can potentially help readers to make an informed decision about the right choice of platform, depending on their needs.**

I. Introduction

Human decision-making is the process of evaluating information and selecting a course of action from the available options [1]. Decision-making is a crucial aspect in any domain, whether it be in manufacturing, health-care, or sales [2]. Through informed decisions, processes can be optimised, improvements made, goals met, and resources smartly allocated. Human emotions or uncertainty, can interfere with the process of decision-making. Poor decision-making can lead to inefficiencies and problems, particularly in manufacturing and healthcare where time-critical and important decisions often have to be made. Incorporating data into the decision-making process, also known as data-driven decision-making, provides insights for evaluating options and choices, minimising biases, and maximising the potential for positive outcomes. Data-driven decision-making utilises artificial intelligence and big data to inform these decisions [3].

Data analytics makes it possible to extract valuable insights from data, make informed decisions, and drive innovation. The capabilities of data analytics are divided into four consecutive stages [4]: descriptive, diagnostic, predictive and prescriptive where the degree of automation increases and the influence of the human decreases per stage. Descriptive analytics [5] involves analysing historical data to gain insights into past events. It provides information about what has happened in the past to assist the process of data-driven decisions based on historical patterns. Diagnostic analytics [6] identifies the underlying reasons for specific outcomes or issues. It combines historical data and statistical techniques to find patterns, correlations and anomalies. This provides actionable insights to troubleshoot and optimise processes. Predictive analytics [7] attempts to forecast future trends, events, and outcomes. While the previous two stages focused on historical data, predictions are usually made on real-time data. Predictive analytics is a crucial component for data-driven decision-making and forecasting future events. Once a prediction is made, there are often countless ways to proceed. In addition, the decision to be made is often time-critical and associated with human uncertainty. To ensure that no human error occurs at this critical point and cancels out the previous analytics steps, prescriptive analytics is used [8]. The objective of prescriptive analytics is to provide decision recommendations for action support or full decision automation, eliminating the need for human intervention in decision-making. It is the most advanced form of decision support systems. To give a practical example: In a manufacturing context, prescriptive analytics could involve analysing historical production data to predict future demand and potential machine failures. Based on these predictions, the system might recommend optimal production schedules, machine assignments, and resource allocations. The quality of the decision is heavily based on the quality and consistency of the available data and the prediction algorithm. Due to the strong increase in demand for prescriptive algorithms [15], the need for user-friendly interactions has also increased. Prescriptive analytics platforms combine data management and processing, all previous data analytics levels and actionable recommendations. Data is either provided in form of historical data or data streams that are directly processed. A platform provides a user interface, to view the data and the recommended actions. Additionally, platforms should incorporate user feedback into their recommendations. A high-level representation of a prescriptive analytics is shown in Fig. 1. The illustration anticipates the following literature research, however it serves as an effective introduction to the topic. The individual components of the platform have been created by superimposing many of the platforms presented in the literature. In all cases, the starting point is a domain-dependent data source and data is continuously transferred to a database through various protocols. The choice of protocols is again application-specific, e.g. MQTT for industrial transmission. The databases are based on either SQL or No-SQL; we

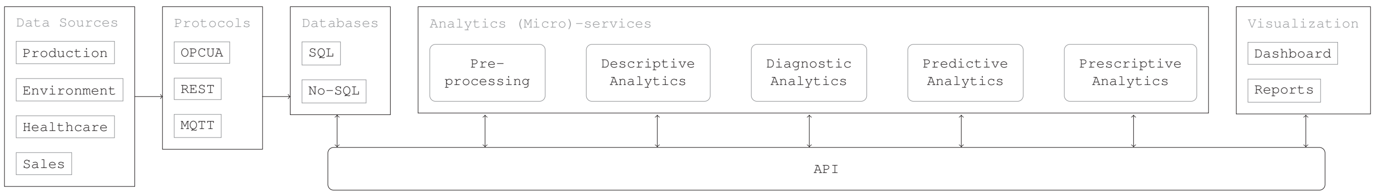

Fig. 1. High-level view of typical components of a prescriptive analytics platform based on [9], [10], [11], [12], [13], [14].

will delve into this later in this paper. The individual services communicate with the databases and the visualisation through an API to provide actionable recommendations or automated actions.

A. Background and Definitions

To enable us to carry out a precise literature review, we identify related research topics and define the boundaries of our paper.

1) Distinguishing Between Platform, Framework and Architecture: A platform serves as a basic environment that includes both hardware and software elements on which a program is executed [16]. A framework, on the other hand, is a reusable set of tools, libraries and standards designed to streamline application development by providing predefined structures [17]. Architecture, in this context, refers to the high-level design decisions that determine the overall structure of a software system and govern the interaction of components and data flow [18]. Although these concepts are linked, they have different functions: A platform defines the execution environment, a framework facilitates development, and the architecture outlines the structural organisation of the system, while the focus of this work lies on platforms.

2) Prescriptive vs Recommender vs Expert Systems vs Data-Driven Decision-Making: The concept of data-driven decision-making bases the decision-making process on data and information from different sources. This makes the decision-making process more consistent, unbiased and efficient, compared to a human decision based on intuition and influenced by feelings [19]. Data-driven decisions provide insights to evaluate options when decisions are time-critical, maximising the potential for positive outcomes. This leads to informed decisions, reducing poor decisions and inefficiencies.

Recommendation systems are common in everyday life, such as recommending a song on Spotify or a movie on Netflix based on previous user behaviour. Building on the foundation of data-driven decision-making, recommender systems present a practical application of decision-making algorithms. Nowadays, recommender systems can be found everywhere. For example, recommender systems are employed in E-commerce to suggest products to customers based on browsing history, purchase history and what other similar users have viewed or purchased. The power of recommender systems lies in the personalised decisions they can provide [20]. Utilising many different types of data sources, they are able to provide recommendations going further than generic recommendations, that fit to a provided scenario. Furthermore, they can factor in a given strategy provided by the user [21]. An example of a strategy influencing the recommended action, generated by an algorithm, is the scenario of a failed machine in a production environment.

Prescriptive analysis incorporates aspects of Recommender Systems, as it not only predicts future events, but also prescribes actions to reach the best possible outcome. For this purpose, prescriptive analytics applies data analytics techniques, such as prediction, optimisation algorithms, machine learning and simulation algorithms. The main difference of these two narrowly related concepts lies in the way decisions are made. Recommender systems personalise the user experience by generating personalised recommendations. Prescriptive analytics deals with the optimisation of decisions and tries to find optimal solutions for complex problems, by using predicted data, machine learning algorithms, Simulations and prescriptive algorithms [22].

Another closely related concept are expert systems. Expert systems try to emulate the decision-making process of a human expert, with the aim of solving complex problems with reasoning and knowledge [22]. They are meant to assist humans in complex situations, rather than to replace them entirely. Expert systems lack general knowledge, as they are very specialised which makes them difficult to adapt to different situations. Instead of performing arithmetic operations or calculations, they use knowledge and reasoning to solve problems.

3) Microservice vs Monolithic architectures: For the operation of a prescriptive platform, it is necessary to choose an architecture that defines the structure of the software for the platform. A basic distinction can be made between two types of architecture: monolithic and microservice architectures. A monolithic architecture is a traditional model of a software programme that is built as a single, self-contained unit that is independent of other applications. This type of architecture is ideal for small projects due to the low overhead. A microservices architecture is an architecture based on a series of independently deployable services [23]. These services have their own logic and database with a specific goal. Updating, testing, deployment and scaling take place within each service. Since prescriptive platforms have to solve many complex analytics tasks, such as training ML models, the properties of microservice architectures are essential. Therefore, we focus on such architectures in this paper.

B. Contributions

Our contributions compared to related work are:

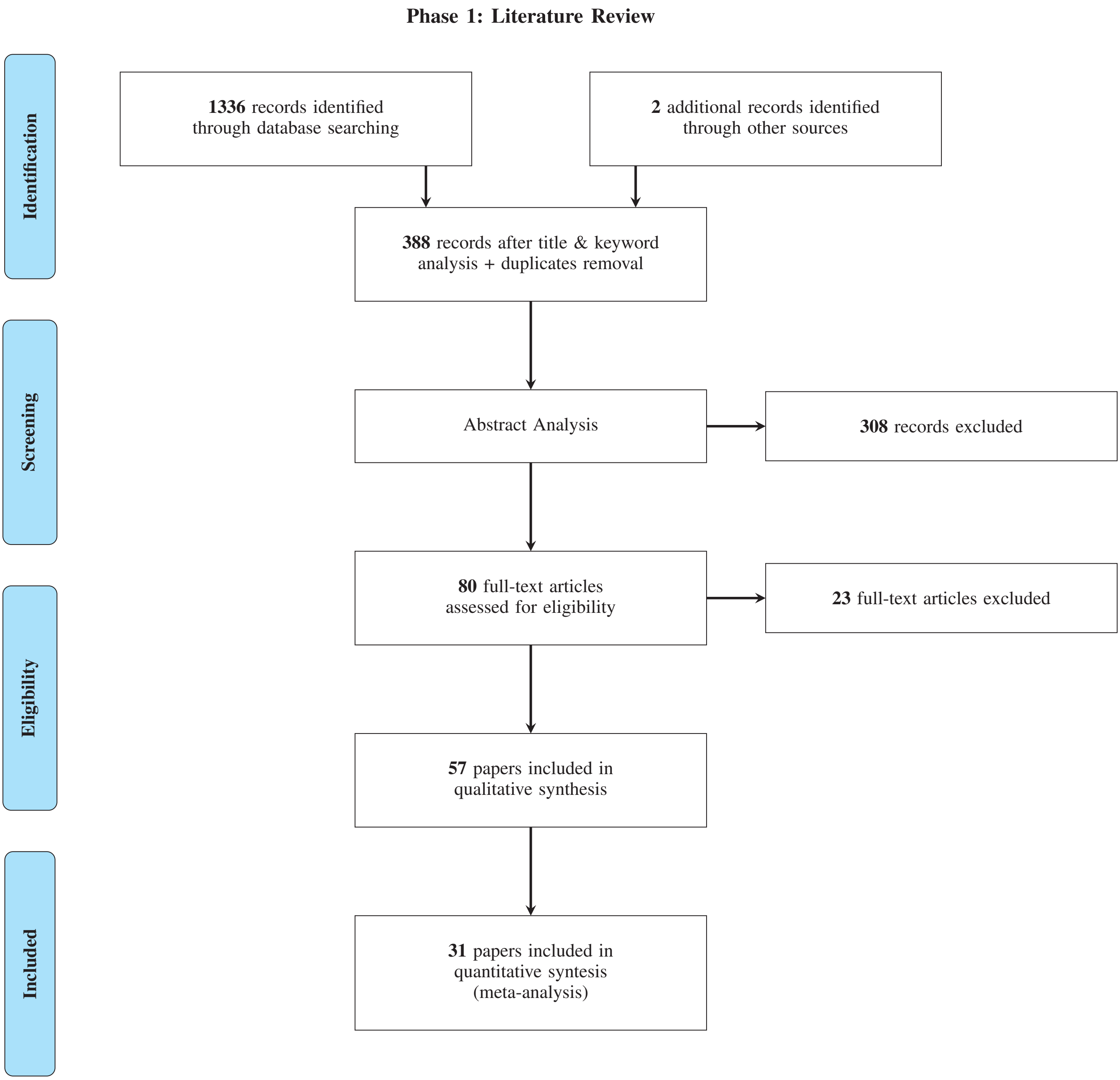

Fig. 2. Phase 1 of the Literature Review pertains to the gathering of relevant papers. The initial results gathered from each database are filtered through three stages, followed by strict filtering according to the inclusion and exclusion criteria highlighted in subsection II-A.

- **Comprehensive review:** We provide the most comprehensive overview of prescriptive analytics platforms. For each platform we provide a detailed description of the respective characteristics.
- **New Taxonomie:** We propose a new taxonomie for prescriptive analytics platforms categorising them based on the technical readiness and key characteristics.
- **Future directions:** We discuss the current technical readiness of prescriptive analytics platforms, current limitations and suggest possible future research directions.

There are several limitations regarding the platforms analysed during the Systematic Literature Review. Many platforms are designed with a very narrow application scope, targeting only specific use-cases or domains, such as healthcare [24]. Furthermore, platforms that incorporate interdisciplinary approaches are scarce and rarely go beyond the conceptual phase.

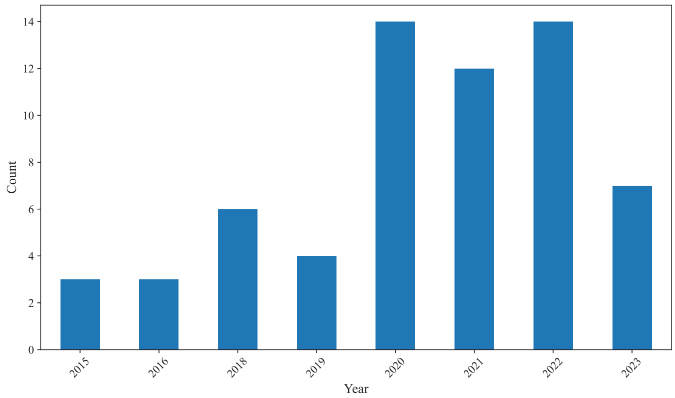

Fig. 3. This bar chart shows the publication years of the various papers, with the majority of papers being published from 2020 onwards

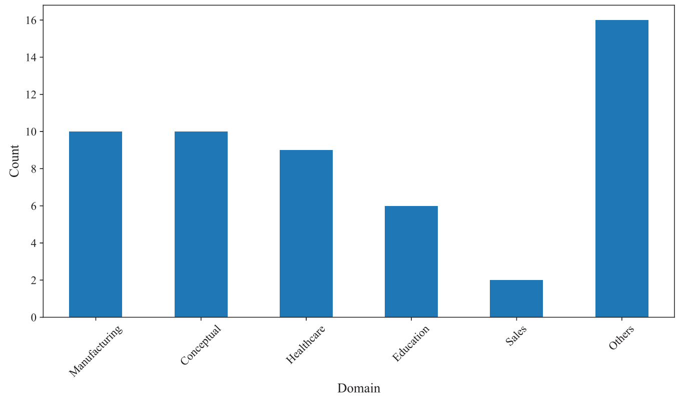

Fig. 4. The bar plot shows the number of papers in each domain, highlighting the interdisciplinary nature of prescriptive analytics platforms. This results in the necessity to make the platform components work with a large number of domains, going beyond the domain of manufacturing. Domains mentioned only once are grouped under "Others".

The rarity of research and development on interdisciplinary platforms, which offer an end-to-end approach from data gathering to the prescriptive component, identifies a significant research gap. This paper aims to address this gap, highlighting the necessity for further research, as no existing study comprehensively meets these criteria.

Currently, there are no other review papers pertaining to prescriptive analytics platforms in the databases searched during the Literature Review (Fig. 2).

II. Methodology

We perform a systematic literature review as described in [25], to examine and summarise existing prescriptive analytics platforms. The literature search was conducted between [August 2023] and [December 2023], focusing on studies published between 2015 and 2023 to ensure the relevance of the findings. Furthermore, the literature review is structured into two phases. Within the first phase, shown in Fig. 2 we identify the most relevant literature. This phase contains three steps that build up on each other to filter out all non-relevant literature, such as papers which only mention the search terms because of future work (outlook) or because they explain the concept but do not actually apply the mentioned method. Furthermore, literature surveys were discarded from the results. Within the second phase we then divide the remaining papers into different categories to build a taxonomy.

A. Research question formulation

The Structured Literature Review is guided by three research questions:

- **RQ1:** Which prescriptive algorithms are available and how can they be effectively integrated into a prescriptive analytics platform to generate actionable recommendations?
- **RQ2:** What are the core components required to build a cross-domain prescriptive analytics platform?
- **RQ3:** Which software options are suitable for implementing core components within a prescriptive analytics platform?

B. Publisher and search strings

The included databases were IEEE, Springer, ACM and Web of Science, which are known for their extensive collection of research pertaining to technology and computing. The search strings were extracted from the research questions established in subsection II-A. This led to the main term 'prescriptive'. To widen the search, while maintaining relevance to the research questions, 'Prescriptive' was concatenated with the terms 'Analytics', 'Platform', and 'Microservice'. This approach led to the formation of the following search string: *(prescriptive) AND (analytics OR platform OR microservice)*. The focus of the literature review was further narrowed by establishing inclusion and exclusion criteria. Included were results in which the topics of the search string were the primary subject and lay within the domain of prescriptive analytics. Exclusion criteria were set to omit surveys and non-English publications.

C. Results

The search string yielded a total of 1336 papers. Fig. 2 shows the three stages of the first phase of the literature review and the number of research papers in each stage. The structure of the chart is based on the PRISMA Flow Chart [26], to summarise the screening process and to secure transparency and the quality of the review [27]. Firstly, all papers obtained from the search strings were saved. The first stage of filtering consisted of a title and keyword analysis, as well as a duplicate deletion process. In this stage, 388 relevant papers were identified. Of the 412 initial Springer-papers a lot of mismatches were identified and only 91 remained. From the 299 ACM results, only three papers were identified as relevant. The low yield of relevant papers in comparison to the total results could potentially be attributed to the search algorithm employed by the ACM database, which likely relies predominantly on keyword matching. Furthermore, it is plausible that the ACM database is not the most suitable source for research on this particular topic. For the IEEE database, 100 out of 129 papers passed the title and keyword analysis. Web of Science yielded the most results of all databases with very good keyword-matching. The reason for the low yield for Web of Science can be attributed to the duplicate screening, as Web of Science was the last database to be considered and Web of Science also queries IEEE, which resulted in a lot of duplicates. Furthermore, review articles are excluded.

In stage 2, the abstracts of the remaining 388 papers were screened. This resulted in 80 relevant papers, none of which came from the ACM database. In stage three a full-text read and forward & backward search was performed on the 80 remaining papers. This yielded a total of 57 relevant papers from the four publishers. To also cover work from other publishers, we used Web of Science (WOS) to aggregate our results. **This process resulted in 57 relevant papers that are considered key literature in the field of prescription up to the present date.**

In Fig. 3, the publication year of the 57 relevant papers is shown. A continuous trend of growth in the field of prescriptive analytics is observed, with most papers being published within the last three years, indicating an increased interest in prescription. Fig. 4 shows the distribution of the 57 relevant papers across various domains. Many papers fall under the 'Conceptual' category, as they present general approaches. The most dominant research areas within the field of prescriptive analytics are the domains of 'Manufacturing', 'Healthcare', and 'Education'.

Domains: In this context, domain refers to a specific area of expertise or industry. The main domains identified during the literature review include 10 papers in the field of manufacturing, nine for healthcare, six for education and two for sales. Conceptual means that the paper did not include any implementation, or that the implementation is not domain-specific. There are also other domains that could be identified. As they occurred only once, they are grouped under the keyword "Others".

In the 'other' category, a wide range of domains represented by 16 individual papers are grouped. Notable domains include Aquaculture with a focus on Model-based Approach to Pricing (MAP) for crab pieces [28], Logistics exploring a Process-aware Recommender System for optimising KPIs [29], Bioinformatics enhancing user interface for accurate information presentation in prescriptive systems [30], Automotive discussing requirements for prescriptive recommender systems for EV battery longevity [31], and Mobile Edge Computing developing a framework for MEC Orchestration [32].

Our Position: Prescriptive algorithm and their implementation into platforms is of increasing interest in recent literature. Unfortunately, in many cases it is merely used as a buzzword without actual implementation of prescription. This results in a disconnect between the anticipated progress in research and its real-world application.

III. Taxonomy

Many of the analysed platforms vary significantly from one another. Some platforms can be used for a variety of use cases, while others are designed for a single specific use case only. Additionally, the maturity level of the platforms differs extensively.

In stage 2 of the literature review, shown in Fig. 5, the papers underwent a second filtering. This step focuses on the papers containing a prescriptive analytics platform and classifying them as *prescription, conceptual frameworks & architectures, and validated platforms*, to organise the diverse information presented by these papers and group them based on their maturity level. Moreover, this facilitates easier comparative analysis and enhances the relevance of the findings. After the filtering and classification 16 platforms remained and 15 highly relevant papers regarding Prescriptive Analytics. Conceptual Frameworks represent the theoretical platform concepts, are not implemented and provide the basis for the validated platforms. Intended uses cases and func-tionality is presented. Conceptual Frameworks, for instance, may only reference the use of a 'database', while validated platforms provide further details, specifying the exact type of database used in the platform. The most informative papers regarding the general topic of prescriptive analytics general were grouped under 'Prescription'. From the final selection of papers, all relevant information was extracted and consolidated into a spreadsheet document.

A. Definition of prescriptive analytics

Prescriptive analytics represents the highest and most advanced form of analytics, building on descriptive, diagnostic and predictive analytics. Different definitions and interpretations of prescriptive analytics can be found in the literature. To find a common basis, we use Gartner's 7-step model for hybrid decision-making [33]. These seven levels are sorted into three categories: decision support, decision augmentation and decision automation. The decision support category contains the first two levels of human decision support and advisory. Here, the human performs the actions on his own and is only supported by data in the decision-making process. At the next stage of decision augmentation, humans and AI work together so that the human can simply confirm or veto the action. The highest form of prescription is complete decision automation. Here, humans are only involved in regular audits or are not involved at all.

According to one paper, prescriptive analytics involves the use of optimisation and simulation algorithms to recommend actions for the most effective outcome in a decision support system. Furthermore, according to [34], prescriptive analytics can be used to prescribe interventions, to prevent an undesired outcome, based on real-time data. [35] defines Prescriptive Analytics as extending predictive analytics by not only predicting scenarios but also using the prediction as a basis for applying data analytics to historical and real-time data in an optimisation stage. This approach allows for automatic planning and task allocation, for example, in the context of prescriptive maintenance.

> **Our Position:** None of the papers we identified in our literature search went further than decision augmentation, with the majority only performing decision support. This shows that the research field is still largely in its early stages of development.

B. Prescriptive Algorithms

While performing the literature review, it became apparent that a significant disparity exists in the level of detail provided by the authors of the papers, especially concerning the algorithms used. Often the term *recommender system* or *decision support algorithm* is mentioned but no algorithm is explicitly mentioned.

In one paper by Rizzo (2022), a *Deep Q-Network* is used together with dynamic programming to optimise Air Cargo Revenue [36]. Lamrini (2023) uses the *TOPSIS* technique (which stands for ”Technique for Order of Preference by Similarity to Ideal Solution”) to solve a multi-criteria decision problem in a big data context [37].

Satyanarayana (2019) uses ensemble classification to minimise grading bias in academia. Based on a prediction of student performance, recommendations are made such as to seek additional help or to partner with a high-performing student [38].

Further algorithms that were mentioned are linear programming models [39], Evolutionary Optimisation [40], mathematical or constraint programming [41], Prescriptive Support Vector Machines (PSVM) [42], One-Class Support Vector Machine [35] and Non-dominated Sorting Genetic Algorithm II (NSGA-II), as well as Reference-point-based NSGA-II (R-NSGAII) [43]. Furthermore, probabilistic models, machine learning or data mining, evolutionary computation, simulation, and logic-based models form the basis for both predictive as well as prescriptive analytics [44].

C. Conceptual Frameworks

A total of ten papers were categorised as conceptual. A noteworthy paper is titled *Building an Industry 4.0 Analytics Platform* [10]. This paper is of special interest as the platform was developed for the multinational engineering firm *Bosch*, which implies that the company has extensive experience in the field of Industry 4.0. The platform is based on a *Lambda Architecture* approach and is designed to handle large volumes of data, enabling prediction and prescription at the scale of Bosch's global manufacturing network. The tools used in the platform are not explicitly mentioned. However, it is stated that extensive use is made of open-source tools, such as those from the Hadoop ecosystem.

A different paper, for example, focuses on Operational Data Analytics (ODA) within the context of High-Performance Computing. Its goal is to combine two frameworks: the ”Evolutionary Model of Analytics Capabilities” (as mentioned in section I) and the ”Four-Pillar Model for Energy-Efficient HPC Operations.” This results in a continuous stream of actionable insights that can be further utilised. The framework is validated by applying it to find the optimal settings for certain aspects of running HPC infrastructure, such as cooling technology and optimal inlet temperature, to achieve efficient cooling while also running the infrastructure as efficiently as possible [45].

Another paper proposes a novel approach to prescriptive analytics by using Interactive Multi-Objective Reinforcement Learning (IMORL). According to the authors, this approach has several benefits: it incorporates user feedback through approving or rejecting recommendations, and it can dynamically adapt the model to a user's strategy by retraining the model. The approach is validated by applying it to a stock market use case, although it is not limited to this specific scenario [46].

D. Validated Platforms

From the selection of papers, six papers were classified as containing a validated platform. One paper [47] develops an IIoT platform for automated error detection in industrial hairpin welding. Key components of this platform include a container architecture and MQTT as the connection layer between the platform's modules. An Azure SQL Database is used for data storage. The authors utilise a CNN to predict welding defects, and issue recommendations based on the detected defects. Furthermore, the authors validate the system by comparing their edge computing solution to a cloud computing solution, and observe a significant runtime reduction of 85%.

A concept matrix (Table I) was developed that systematically outlines the key points of each platform. This was only done for all the validated platforms because these concepts contain specific software components. Such a selective approach was essential to achieve a certain depth of understanding and insight. Furthermore, we ensure that the chosen papers are based on established and proven concepts. Extracted information pertains to the type of input data supported by these platforms (e.g. sensor data), protocols used for data transfer (e.g. MQTT), the database used (e.g. SQL), and whether the platform runs on the edge or in the cloud.

The matrix columns are based on Figure 1, therefore covering the various aspects of a prescriptive analytics platform. Moreover, the entire prescriptive analytics process—from data gathering and transfer to data management—is represented. Additionally, the 'Data' category denotes the types of data and the inclusion of a pre-processing stage within the platform, while the 'Hardware' category distinguishes between cloud-based and edge computing platforms.

Based on the analysis of the concept matrix, an ideal platform should implement the following aspects. It should first be noted that some of the components mentioned below apply to all data analytics platforms. A prescriptive analytics platform should be capable of handling a variety of input data, such as machine, healthcare or sales data. This ensures that the platform is suitable for a wide range of applications with different requirements regarding input data. However, the platform should not be specific to one domain, for example,

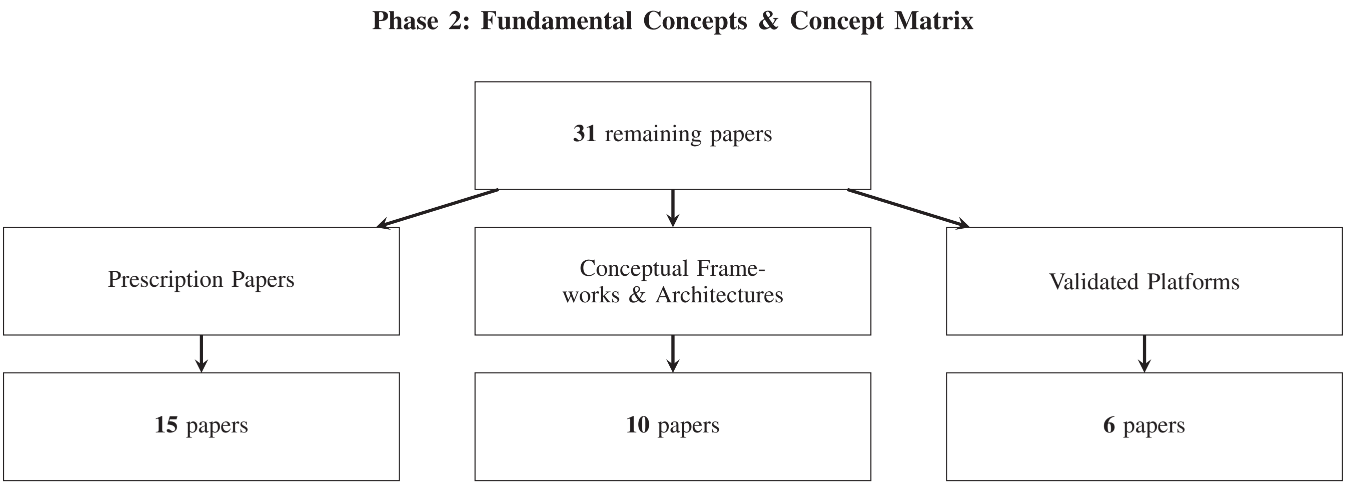

Fig. 5. Phase 2 of the Systematic Literature Review categorisation. The 31 remaining papers are distributed into two main categories based on their maturity level: Conceptual Frameworks & Architectures (10 papers) and Validated Platforms (6 papers), alongside a general category for prescriptive analytics papers, Prescription (15 papers).

manufacturing. Therefore, a generalised prescriptive analytics platform should further be able to process all kind of time series, image, audio or text data to cover various domains and use cases.

In subsection III-A, the 7 levels of hybrid decision making were introduced. The greater the number of levels supported by an ideal platform, the more powerful it will become. Consequently, the platform should ideally support all levels, including the final two decision automation levels. This implies that the platform is capable of offering optimal decision recommendations, providing a veto option, and ultimately, making autonomous decisions.

Furthermore, to be capable of real-time prescriptive analytics, the ideal platform needs to implement different communication protocols. Common protocols used in the industry and frequently observed in different platforms include MQTT, OPC-UA, and a REST API. The transferred data from the different data sources needs to be saved in a robust database, which allows for high volume data and quick access to historical data (for model-building) and live data (for prescriptive recommendations). Lastly, data pre-processing capabilities are essential. These capabilities are crucial for transforming the available data into knowledge, which can be used to generate prescriptive recommendations. The focus of the platform should be on interoperability to facilitate easy integration with existing infrastructure. Additionally, an intuitive UI for user interaction is crucial for presenting all generated prescriptive recommendations, visualising data, and displaying the current operational status of the platform, including load and other operational parameters. However, the aspect of UI-design was not included in the concept matrix. Fig. 6 shows the type of input data supported by the different platforms.

Process data is defined as the parameters of the process itself. For example, this could be a temperature which is set for a melting operation. Machine data, on the other hand, cannot be set and is characterised as data representing the condition

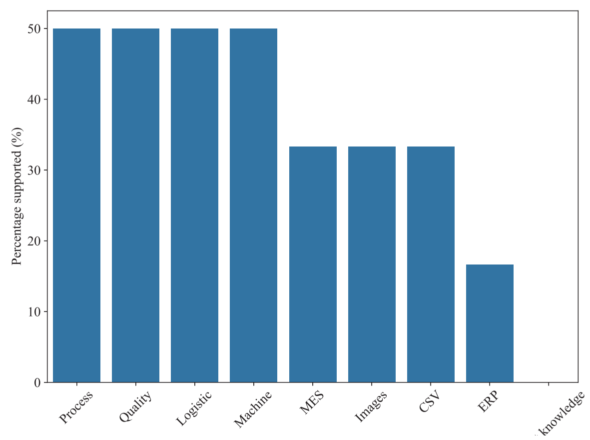

Fig. 6. Distribution of the supported Input Data Types across all validated platforms

of an operation. As an example, this may be the temperature of a motor, which is being monitored to avoid overheating.

MQTT (Message Queue Telemetry Transport Protocol is a protocol widely used for sending sensor data, especially in iot-scenarios. It is open source and works on a publish-subscribe model via an MQTT broker.

IV. Further discussions and future directions

Prescriptive analytics is an important technique in modern businesses and societies, enabling rapid decision-making processes not possible without this technology, as decisions can be made without delay and potential biases introduced by human emotions and uncertainties can be avoided, to the extent that decision augmentation or automation is available. Many decisions can be too complex for humans to find an optimal decision. Therefore, optimisation algorithms can

TABLE I. Concept matrix for prescriptive platforms. We distinguish between different types of input data, protocols, databases, data format and used hardware

	Input Data								**Protocols**			**Database**			**Data**			**Hardware**	
Contribution	Sales Data	Health Data	MES	Process	Quality	Logistic	Machine	Images	MQTT	OPC-UA	Rest	SQL	NOSQL	HDFS	Pre-Processed	Historic	real-time	Edge	Cloud
[47]								X	X			X			X	X	X	X	X
[9]			X	X	X	X	X		X	X			X		X	X	X	X	X
[28]				X	X	X										X	X	X	X
[48]							X							X			X		
[10]			X	X	X	X	X	X					X		X				
[49]							X								X	X	X	X	
[43]					X														
[39]	X														X	X			
[50]		X					X					X				X			
[51]											X				X				
[52]	X	X						X				X			X	X			
[46]																X			
[53]												X			X	X			X
[24]		X												X	X				
[54]							X		X		X	X			X			X	X
[55]		X													X	X	X		

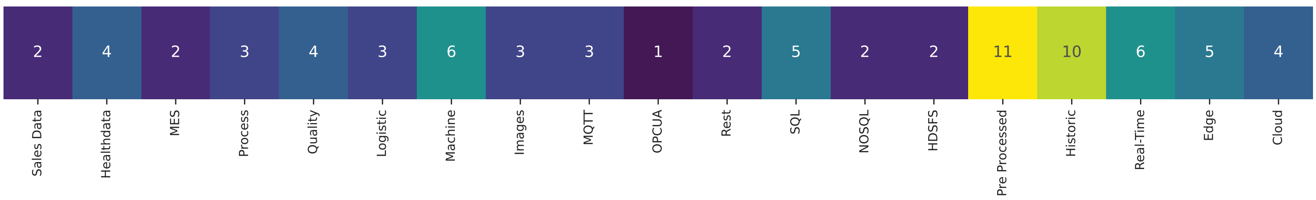

Fig. 7. Visualisation of Table I as a heatmap. Bright shades represent a higher occurrence of the concept elements represented in the concept matrix

provide valuable decision support recommendations. The challenge with prescriptive analytics lies in incorporating it into business processes in a way that makes it possible to reuse the created architecture. Therefore, we have highlighted the core components as well as software components with which this can be achieved. However, potential bias can never be fully removed and this needs to be kept under consideration. There is still the possibility of included bias in the data or the models, impacting the decision recommendations. Consequently, it is important to include transparency into the platform, to be able to achieve accountability and human oversight. Developing prescriptive analytics algorithms and incorporating prescriptive decision recommendations into existing or new processes is a complex topic. However, the analysis in this paper has shown that many parts of a prescriptive analytics platform can be reused and by adopting a modular architecture based on microservices connected through an API easily adapted to different scenarios. However, there is hardly any research into the topic of general prescriptive analytics platforms and the maturity level of existing specialised platforms varies greatly. The SLR could not find a single survey paper regarding this topic in the included databases. This paper tries to fill this research gap by providing information on the current state of the art as well as portraying the core components of a general prescriptive analytics platform, based on the analysed specialised platforms from the literature review. It is important to consider the full analytics pipeline, from data gathering up to the presented decision recommendation. By providing this platform framework, we hope to form the basis for future modular prescriptive analytics platform as well as future platforms. Existing platforms mostly only incorporate one input data type or protocol and are not modular. Furthermore, the analysis of the platforms has shown that the inclusion of humans in the prescriptive component (as proposed by Gartner, see subsection III-A), is merely a side topic in the analysed papers and platforms and therefore requires further attention.

The SLR was guided by three research questions, which were introduced in subsection II-A. These can be answered with knowledge gained by analysing the various platforms. **RQ1:** There is a wide variety of algorithms that can be employed for use with prescriptive analytics. For optimisation tasks, optimisation algorithms include Evolutionary Optimisation, Linear Programming Models, Mathematical or Constraint Programming, Prescriptive Support Vector Machine (PSVM), Non-dominated Sorting Genetic Algorithm II (NSGA-II), and Reference-point-based NSGA-II (R-NSGA-II). The algorithms should be implemented in a modular architecture, utilising an API interface with the platform.

RQ2: The SLR identified the core components of a prescriptive analytics platform, shown in Fig. 1. Firstly, the platform needs to be connected to a data source. Therefore, the platform needs to support a variety of common data transfer protocols. To efficiently save the data for real-time analysis or historic data, the platform backend needs to implement one or more database types, depending on the kind of data and the universality of the platform. A further core component of a prescriptive analytics platform is the data processing stage. This includes data pre-processing, as well as a component for the different analytics stages, from descriptive to prescriptive analytics. The last component concerns data visualisation and information presentation, such as the output of prescriptive optimisation or decision recommendation. These components are quite similar with general analytics platforms of previous levels such as predictive analytics platforms.

What is really important for prescriptive platforms are components that provide user-friendly and accurate indications of response strategies and, depending on the level of maturity, execute them in collaboration with a human or do this completely autonomously as this represents the difference from a non-prescriptive analytics platform. The SLR has shown that the prescriptive component is implemented very differently, and the degree of decision support (or automation) differs greatly and by use-case. Therefore, all stages of decision support should be supported by the prescriptive component of a prescriptive analytics platform.

RQ3: Essential software components identified during the analysis include OPC-UA, REST, and MQTT for data transfer. These are common protocols used by many platforms. As a database solution, the platforms each work with a different database. This could be MySQL, PostgreSQL, or an Azure SQL database service. For the components to work together and to be interchangeable, a platform architecture needs to be flexible. This can only be achieved by using a microservice architecture and connecting the different stages/components of the platform via an API. This allows each component to be easily interchangeable while also providing the ability to adapt the platform to the type of data of various use-cases for the platform.

Limitations: There are several limitations and aspects to consider when working with prescriptive analytics. Data requirements are significant for prescriptive analytics algorithms to be effective, large amounts of data need to be available. This can be a problem for new applications or small-scale applications. Furthermore, expert knowledge is often needed for the successful implementation and interpretation of prescriptive analytics. This includes domain-specific knowledge, as well as expertise in data science and analytics. Moreover, to achieve good accuracy and reliability in the prescriptive decision recommendation, accurate predictive models are needed. This can be challenging, especially in industrial fault detection.

Future research directions We expect the adoption of Large Language Models (LLMs) in the future for prescriptive analytics platforms, not just for generating decision recommendation, but also to interface with the user of the prescriptive analytics platform. By incorporating LLMs into platforms, the usability of the platform increases and decision recommendations can be generated in plain text, making it easy for the user to understand. Furthermore, LLMs provide the ability to integrate feedback loops into the platform, creating the ability for users to give feedback and therefore improve the relevancy of the decision recommendations. LLMs are both generalised but can still be tailored to a specific use-case. However, the explainability of LLMs still needs further research.

V. Conclusions

This paper aims to draw the attention of researchers and experts to the potential of prescriptive algorithms for recommending actions, how they can be integrated into prescriptive platforms in a user-friendly way and to what extent prescriptive platforms are technically ready. To support our positions, we have reviewed the relevant literature in a systematic literature review in order to close existing gaps. Our objective is to identify existing prescriptive algorithms and their implementation into a platform to provide recommendations. Further, we identified the core components of prescriptive platforms and their technical level of readiness. If this paper contributes to a new research direction regarding interdisciplinary prescriptive analytics platforms, it will have fulfilled its purpose.

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