

Analysis of risks related to the use of artificial intelligence in production planning and control processes using fuzzy FMEA

Üretim planlama ve kontrol süreçlerinde yapay zekâ kullanımına yönelik risklerin bulanık FMEA ile analizi

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Abstract

Production planning and control (PPC) processes are increasingly subject to uncertainty due to growing system complexity, variable demand, and the integration of data-driven decision-support tools. Artificial intelligence (AI)-supported tools provide significant conveniences in managing this uncertainty, but also give rise to new risks that are difficult to control. However, the literature mainly addresses the risks posed by AI in PPC in a scattered manner through different concepts, and comprehensive approaches that holistically assess these risks remain limited. This study aims to address this gap in the literature by assessing the risks arising from the use of AI in PPC applications using Fuzzy Failure Mode and Effects Analysis (Fuzzy FMEA). In this context, the nine risk factors within the scope of the study were analysed using linguistic assessments by 14 academics specialising in PPC, with respect to probability, severity, and detectability. The analysis results identified cybersecurity, lack of explainability, and algorithmic bias as the most significant risks associated with AI use in PPC applications. The study offers a structured risk-prioritisation approach under uncertainty, providing a guiding framework for a more controlled and sustainable integration of AI into PPC processes.

Keywords: Production Planning and Control, Artificial Intelligence Risks, Fuzzy FMEA

Jel Codes: C44, D29, J33

Öz

Üretim planlama ve kontrol (ÜPK) süreçleri, artan sistem karmaşıklığı, değişken talep koşulları ve veriye dayalı karar destek araçlarının entegrasyonu nedeniyle giderek daha fazla belirsizliğe maruz kalmaktadır. Yapay zekâ (YZ) destekli araçlar, bu belirsizliğin yönetiminde önemli kolaylıklar sağlasa da kontrolü güç yeni riskler ortaya çıkarmaktadır. Buna karşın literatürde YZ'nin ÜPK'de oluşturduğu riskler farklı kavramlar üzerinden dağınık biçimde ele alınmakta ve bu riskleri bütüncül bir şekilde değerlendiren yaklaşımlar sınırlı kalmaktadır. Bu çalışma, ÜPK uygulamalarında YZ kullanımıyla ortaya çıkabilecek riskleri Bulanık Hata Türleri ve Etkileri Analizi (Bulanık FMEA) ile değerlendirerek literatürdeki bu boşluğu gidermeyi amaçlamaktadır. Bu doğrultuda çalışma kapsamında tanımlanan dokuz risk faktörü, ÜPK alanında uzman on dört akademisyenin olasılık, şiddet ve tespit edilebilirlik boyutlarındaki dilsel değerlendirmeleri üzerinden analiz edilmiştir. Analiz sonuçlarında siber güvenlik, açıklanabilirlik eksikliği ve algoritmik önyargı ÜPK uygulamalarında YZ kullanımına ilişkin en önemli riskler olarak belirlenmiştir. Çalışma, belirsizlik altında yapılandırılmış bir risk önceliklendirme yaklaşımı sunarak YZ'nin ÜPK süreçlerine daha kontrollü ve sürdürülebilir biçimde entegre edilebilmesine yönelik yol gösterici bir çerçeve sunmaktadır.

Anahtar Kelimeler: Üretim Planlama ve Kontrol, Yapay Zekâ Riskleri, Bulanık FMEA

JEL Kodları: C44, D29, J33

Submitted: 2/01/2026

Revised: 8/02/2026

Revised: 20/02/2026

Accepted: 1/03/2026

Online Published: 25/03/2026

Citation: Duran, Z., Analysis of risks related to the use of artificial intelligence in production planning and control processes using fuzzy FMEA, *bmij* (2026) 14 (1):312-328, doi:

<https://doi.org/10.15295/bmij.v14i1.2705>

Introduction

Production planning and control (PPC) activities are becoming increasingly challenging in contemporary manufacturing systems due to rising complexity, dynamic production conditions, and volatile market structures (Usuga Cadavid et al., 2020, p. 1531). The growing demand for customised products, intensified pressure to reduce costs, and tightening time-to-market targets further reinforce this challenge by pushing PPC into a structure that requires more frequent revisions within narrower time windows. In addition, the increasing frequency of factors that disrupt production flow, such as machine failures, order fluctuations, and unpredictable job arrivals, together with the dynamic reconfiguration of production procedures to meet customer expectations, is transforming PPC into an adaptation process that focuses on managing deviations to maintain flow continuity rather than merely generating plans (Del Gallo et al., 2023, p. 1). For this reason, PPC in industrial practice is no longer regarded solely as a planning activity. However, rather as a process domain that seeks to mitigate the effects of disruptions and uncertainties on production flow and that, although often treated with deterministic assumptions in practice, in reality proceeds in close interaction with deviations and uncertainties (Seeger et al., 2022, p. 8), and this reality makes it necessary for PPC approaches to be based not on static plan generation but on continuous monitoring, rapid replanning, and flexible decision-making capabilities.

In this complex and demanding production environment, artificial intelligence (AI) based tools are increasingly coming to the fore as a strong enabler for PPC in the face of growing data volume, variety, and variability. In particular, the ability to process a large volume of operational data simultaneously, to capture complex patterns, and to adapt rapidly to changing production conditions makes AI more attractive than classical deterministic and rule-based PPC applications. Indeed, the literature emphasises that AI applications offer essential advantages in terms of flexibility and responsiveness across areas such as demand forecasting, production scheduling, capacity utilisation, and performance monitoring (Roblek et al., 2024, p. 2). For example, AI forecasting models can generate more stable predictions by capturing complex patterns such as seasonal and promotion effects that are missed by classical time series applications, thereby enabling improvement in material planning in a way that reduces the threat of excess inventory or stock-out in Material Requirements Planning (MRP) outputs (Elbasheer et al., 2022, pp. 1906-1907). Similarly, performance monitoring applications using sensor and Manufacturing Execution System (MES) data make deviations, anomalies, and bottlenecks signals visible at an earlier stage, enabling intervention before they become errors and directly supporting process control (Usuga Cadavid et al., 2020, p. 1537).

Although the use of AI in PPC processes offers many advantages, it also entails certain disadvantages and risks when production system conditions are taken into account. At the core of this situation lies the fact that the effective and successful use of AI tools in PPC processes largely depends on the quality, consistency, and continuity of data. However, data obtained under real shop-floor conditions are often incomplete or delayed and may include manual interventions and inconsistencies across systems. Indeed, studies on the use of AI in PPC applications report that model performance is tightly linked to data preprocessing activities that are often invisible yet costly (Cadavid et al., 2019, pp. 387-388). At the same time, the dynamic nature of PPC systems raises questions about the sustainability of AI model performance. A model that demonstrates a high level of adaptation to shop-floor conditions during the learning phase may quickly lose that adaptation when the production environment changes. Given that PPC already operates within a narrow time window, this problem can become a difficult-to-tolerate disadvantage in practice (González Rodríguez et al., 2020, p. 1258). This issue is significant from the perspective of explainability and governance. In particular, the opacity of decision mechanisms in methods such as deep learning makes it difficult to anticipate undesired behaviours in advance and to constrain them safely (Burggräf et al., 2018, p. 83). On the other hand, production decisions are not shallow enough to be reduced to a single correct answer. Even under similar conditions, experts may differ in their interpretations. For this reason, outputs from AI tools may not fully satisfy all stakeholders in planning and control processes, thereby undermining trust (González Rodríguez et al., 2020, pp. 1269-1270). Therefore, although the difficulty of managing breakdowns, order fluctuations, and unpredictable jobs makes the use of AI tools attractive in PPC processes, these tools also entail risks that can directly affect the production process (Del Gallo et al., 2023, pp. 12-13).

AI has emerged as a prominent application and research area in the digital transformation of industrial processes in recent years, driven by the increasing volume of data and advances in computational power (Carpanzano & Knüttel, 2022, pp. 1-2; Usuga Cadavid et al., 2020, pp. 1531-1532). In this context, recent studies on the use of AI in PPC processes emphasise the advantages of AI-supported tools while also highlighting practical challenges, including data quality, explainability, and organisational alignment

(Fries et al., 2025, pp. 299-301; Roblek et al., 2024, pp. 3-5; Colangelo et al., 2022, pp. 496-497). Nevertheless, the risks associated with the use of AI in production processes are discussed in the literature primarily in a limited and fragmented manner and are not systematically addressed (Mäule & Götte, 2025, pp. 1254-1255; Plathottam et al., 2023, p. 14; Laska & Karwala, 2023). Moreover, since the conceptual standard has not yet been established, difficulties and dangers can also be expressed with synonymous concepts. To address this gap, the present study provides a structured framework for prioritising and managing risks by comprehensively assessing those arising from AI use in PPC processes through the Fuzzy Failure Modes and Effects Analysis (Fuzzy FMEA) approach. FMEA is a widely used risk assessment tool that systematically identifies the effects of potential problems on process performance. Since decisions in PPC processes progress through interdependent steps, disruptions related to AI usage often go beyond a single technical issue. They can spread throughout the process, affecting plan accuracy, plan stability, and execution performance. Therefore, FMEA has been evaluated as a suitable tool for prioritising AI-related risks and has been chosen for this study. However, because the levels of these risks cannot be quantified with precision in most cases, assessments are inevitably based on expert judgment. To account for this uncertainty throughout the assessment process, the FMEA steps were performed using fuzzy logic.

The remainder of this study is organised as follows: First, an overview of the literature on AI usage in PPC is presented, and the current state of risk discussions in this context is summarised. Next, the research design, the linguistic scale used, the fuzzy FMEA calculation steps, the risk factors evaluated, and the study group are explained in detail. In the following section, the risk assessment procedures are detailed, and the findings are discussed in the context of PPC. Finally, the study concludes with key findings, practical recommendations, and areas for future research.

Literature

The literature on the use of AI in PPC processes has expanded markedly in recent years due to rapid developments in the field, and a significant portion of studies has focused on AI's potential contributions to operational performance. In this context, both empirical and conceptual studies have shown that machine learning based approaches can increase forecasting accuracy in functions such as demand forecasting, production scheduling, and capacity planning, and can provide computational advantages in complex problems (González Rodríguez et al., 2020, pp. 1257-1259; Roblek et al., 2024, pp. 3-5), and it has been emphasised that the data-intensive nature of PPC and the need for real-time decision making render these processes a critical domain for AI applications (Oluyisola et al., 2020, p. 2; Colangelo et al., 2022, p. 496). Nevertheless, it is not sufficiently clear how these contributions have been tested in the literature, or to what extent their validity has been demonstrated under real-world production conditions. Indeed, systematic literature reviews reveal that a substantial portion of AI use in PPC studies focuses on technical performance indicators, and that applications are mainly evaluated in controlled or limited scenarios (Usuga Cadavid et al., 2020, pp. 1534-1536; Seeger et al., 2022, p. 5). Additionally, the absence of an agreed conceptual standard in this research stream means that similar difficulties and risks are often expressed through partially overlapping, near-synonymous constructs (e.g., challenges, barriers, limitations, risks, pitfalls, failure factors). This terminological ambiguity complicates the accumulation of comparable evidence across studies. It contributes to a dispersed, fragmented view of the problem space, making it harder to delineate precisely what is being tested, under what operational conditions, and with what implications for PPC practice.

The integration of AI technologies into PPC processes is a trend documented in the literature that is reported to strengthen the effectiveness of production systems and yield advantages such as increased productivity, balanced inventory levels, and improved failure prediction. However, some studies indicate that these contributions do not occur to the same extent across enterprises and processes, and that factors may impede the achievement of targeted outcomes during implementation. For example, Wan et al. (2021), in their study on AI-supported scheduling and reconfiguration applications in smart factory environments, report that deficiencies, delays, and inconsistencies in sensor data can degrade the accuracy of PPC decisions and lead to fluctuations in planning performance. Sinha and Lee (2024), in their research on the development and deployment of industrial AI applications, note that managers approach models that are insufficiently validated or explainable with caution in decision-intensive processes such as production planning and control. On the other hand, integrating AI-based PPC systems with existing production information systems is also a significant issue in the literature. For example, Kunecová et al. (2025), in their research on European manufacturing firms, find that deficiencies in enterprise information systems and digital infrastructure limit the scope and effectiveness of AI applications; consequently, the operational benefits remain low when AI solutions

are used in isolation within PPC processes. These studies clearly demonstrate the importance of data quality in production environments for the reliability of AI-supported planning and control systems.

In the literature, the risks associated with the use of AI-supported tools in PPC systems are addressed indirectly, typically examined through adoption barriers and readiness conditions. For example, Godinho Filho et al. (2025) systematically analyse the key barriers to the effective implementation of AI in manufacturing and propose a four-level framework comprising 20 barriers. Kunecová et al. (2025), on the other hand, distinguish the role of barriers in the adoption journey by expressing them as absolute barriers, which directly prevent adoption, and relative barriers, which become evident once adoption begins, and position the lack of resources, capabilities, and infrastructure as absolute barriers, while elements such as data quality are positioned among relative barriers. As seen, although studies in the literature highlight obstacles and implementation challenges, they do not provide a systematic risk-based framework for PPC processes. Vyhmeister et al. (2023) also point to this gap, emphasising the need for risk management-based frameworks. However, no studies directly assessing AI risks in the PPC context were found in the literature review conducted in this study.

The literature on risk classification for AI use in production planning and control (PPC) employs diverse labels, conceptualisations, and classification logics, resulting in a fragmented rather than unified structure. For example, Mäule and Götte (2025) identify challenges from 51 review articles and group them into four interconnected categories, namely entry barriers, data-related challenges, complexities related to PPC tasks and their operational integration, and operational constraints. Mäule and Götte (2025) also note that many studies mention challenges only briefly and lack a comprehensive overview. Kunecová et al. (2025), by contrast, approach risk drivers in the broader AI adoption literature for manufacturing mainly as adoption barriers and classify them through different perspectives, such as resource, environment, and usefulness or fit constructs, as well as stage-dependent distinctions between absolute and relative barriers along the adoption process. Godinho Filho et al. (2025), in turn, structure the barrier landscape into hierarchical levels based on interdependencies and propose multi-level frameworks, such as a four-level framework of 20 foundational barriers developed using ISM and fuzzy MICMAC, rather than risk families tailored to PPC functions. Vyhmeister et al. (2023) adopt a governance-oriented lens and address AI-related risks through risk-management standards and trustworthy AI requirements, promoting domain-specific risk-management protocols for manufacturing.

In this study, risks associated with the use of AI in PPC processes were assessed using Fuzzy FMEA to develop this under-explored area in the literature and to provide a guiding framework for the more controlled and sustainable integration of AI into PPC applications. The risk factors considered in the assessment were systematically compiled from the literature and specifically classified for this study. This classification process is detailed in the methodology section. Assessments of the probability, severity, and detectability dimensions of the risks were obtained from PPC and AI experts. Given the inherent uncertainty in expert assessments, the Fuzzy FMEA approach yielded more realistic risk factor ratings and prioritizations, thereby identifying critical risk areas related to AI use in PPC processes and making a valuable contribution to the literature. In this context, the methodological details, risk assessment findings, and study results are presented in the following sections.

Methodology

This section outlines the study's methodological framework and materials. It first presents the rationale for the adopted methodology, then describes the risk structure, the study group, the procedural flow, and the ethical considerations.

FMEA method

The FMEA is an analytical method used during the development of products, processes, techniques, services, or systems, as well as during the implementation of corrective actions, to identify existing or potential failure modes at an early stage, rank these failures, and determine those that should be given priority when moving into the improvement phase (Ilbahar et al., 2018, p. 125). It was initially developed and applied for the U.S. Army. It was defined as a reliability assessment technique under the code MIL-P-1629, titled "procedures for performing failure mode, effects, and criticality analysis (FMECA)," aimed at identifying the effects of system and equipment failures (Kahraman et al., 2013, p. 542). In its early years, FMEA was used primarily in the aviation and automotive industries; over time, however, it has come to be applied across virtually all sectors.

In the FMEA method, the relative priority of risks is determined by the risk priority number (RPN), calculated as $RPN = O \times S \times D$, where O denotes the probability of occurrence of a failure, S denotes the

severity of its effect on the system, user, or customer, and D denotes detectability, defined as the likelihood of identifying the failure before its effects occur under existing control mechanisms (Chen et al., 2025, p. 2; Caristi et al., 2025; Kahraman et al., 2013, p. 546). These parameters are scored on a scale of 1-10 in calculating the RPN value, and risks are classified according to the RPN value. The higher the RPN value, the higher the priority the organisation must assign to resolving the failure mode (Chang et al., 2010, p. 285). However, the classification of the RPN value may vary depending on the parameter scale used.

This approach enables risk prioritisation by considering impact severity, likelihood of occurrence, and the capability of current controls to detect failures before adverse effects materialise. However, in this method, O, S, and D are treated as equally important, which does not accurately reflect the differing influence these parameters may have in real-world scenarios (Caristi et al., 2025). The RPN calculation, based on subjective judgments, can lead to different people assigning different scores to the same defect. Moreover, distinct combinations of S, O, and D can produce identical RPN values for failure modes with significantly different risk profiles (Testik & Tok Unlu, 2023, p. 577). This scenario poses considerable challenges for evaluators since two risks with the same RPN might not exhibit the same level of criticality when their individual components are scrutinised. Therefore, traditional FMEA approaches may be inefficient, as they cannot produce sufficiently discriminating and consistent results when prioritising risks. To address these limitations, fuzzy logic has been integrated into FMEA, enabling the quantification of linguistic uncertainties arising from expert judgments and yielding a more consistent, decision-supportive RPN calculation framework.

Fuzzy FMEA method

Fuzzy logic is a computational framework for modelling concepts whose boundaries cannot be sharply defined in the real world, providing a more realistic account of uncertainty. Within this approach, an element's membership in a set is not expressed in an all-or-nothing fashion but rather in a graded manner within the interval [0,1]. In this way, linguistic assessments such as "high", "low", and "acceptable" can be incorporated into analytical models through mathematical representation (Gupta et al., 2021, p. 4). As a result, experts' intuitive evaluations can be analysed within a more consistent and formal framework. Consequently, fuzzy logic provides a practical solution framework for overcoming the above-mentioned limitations of traditional FMEA. Indeed, in a study conducted in the hospital's sterilisation unit, Dağsuyu et al. (2016) compared classical FMEA with fuzzy FMEA and demonstrated that hazards/failures in the unit could be classified and prioritised more sensitively using fuzzy membership functions and decision rules.

The value of fuzzy logic to FMEA has attracted the attention of many researchers, and in recent years, numerous studies have integrated traditional FMEA with fuzzy logic for risk assessment. For example, de Aguiar et al. (2018) represented imprecise information, such as customer requirements and expert opinions, during the product design phase using fuzzy logic, thereby making FMEA-based risk ranking more flexible. As a process-oriented extension of this approach, Rezaee et al. (2018) integrated PFMEA with a multi-stage fuzzy cognitive map to model successive processes in the food industry. They conducted a prioritisation that accounts for causal interactions within and between process stages. Similarly, in applications focused on manufacturing environments, Soltanali et al. (2020) evaluated maintenance and failure risks in an automotive production line using fuzzy FMEA, while Gupta et al. (2021) adopted the same approach to prioritise risks in an industrial system/equipment under uncertainty. Demonstrating that the method can also be adapted across sectors, Testik and Tok Unlu (2023) analysed the types of errors encountered during inspections in test and calibration laboratories using fuzzy FMEA. Following this, Cardiel-Ortega and Baeza-Serrato (2023) applied the fuzzy FMEA approach to support risk assessment in industrial processes; finally, Chen et al. (2025) addressed fuzzy FMEA, along with multi-criteria weighting and inference structures, to prioritise failure modes in a complex technical system.

Fuzzy logic can be used in various ways to incorporate expert judgments involving uncertainty into evaluation processes. In the context of FMEA, the integration of fuzziness in the literature is mostly addressed through rule-based fuzzy inference systems, where linguistic evaluations are modelled using membership functions to produce a risk-priority output, followed by defuzzification. However, the transfer of fuzziness to FMEA is not limited to rule-based approaches. It is also possible to perform fuzzy evaluation by representing the O, S, and D parameters with fuzzy numbers and processing expert judgments with fuzzy arithmetic operations. For instance, Wang et al. (2009) define fuzzy risk priority numbers by treating O, S, and D as fuzzy variables, aggregating them via a fuzzy weighted geometric mean computed via α -cuts and an optimisation model, and then applying centroid defuzzification for ranking. Similarly, Zhang and Chu (2011) propose a fuzzy-FMEA-based prioritisation approach under

uncertainty, combining fuzzy assessments of O, S, and D to obtain fuzzy risk-priority values, which are then defuzzified to produce a final ranking. Since this study aims to prioritise risks by preserving the uncertainty in expert judgments in a traceable manner throughout the FMEA calculation rather than proposing a rule-based inference system, FMEA operations were performed using fuzzy number arithmetic within the scope of the study. In this process, participants' linguistic assessments were converted into triangular fuzzy numbers using the triangular fuzzy number set adopted in the study, and the basic arithmetic operations of fuzzy logic were then applied in subsequent steps.

The triangular membership function is among the most commonly used in modelling fuzzy sets. A triangular fuzzy number is defined by the lower bound (l), the most probable value/peak (m), and the upper bound (u) parameters, as shown in Figure 1.

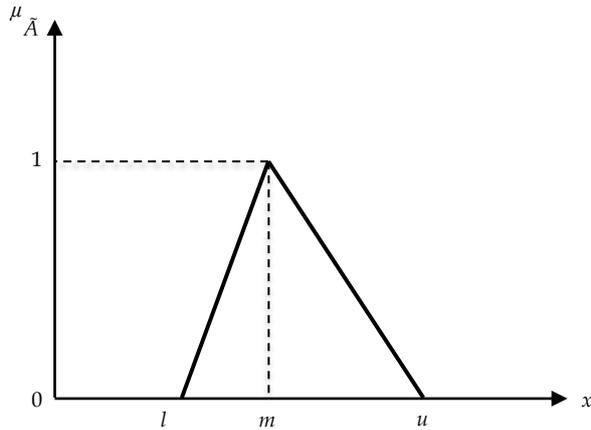


Figure 1: Triangular Fuzzy Number

Triangular fuzzy numbers represent uncertain quantities not as a single definite value but as an approximate range of values consisting of three points. In this approach, the quantity is defined by three parameters, l, m, and u, as shown in Figure 1, and the degree to which each value within the range represents the quantity is expressed gradually through a membership function. Thus, uncertainty is modelled as a graded structure that reflects the relative appropriateness of values within the range. This type of representation allows uncertainty to be formally addressed, particularly in cases such as measurement errors, expert judgment-based assessments, and incomplete/uncertain data. Algebraic operations performed with triangular fuzzy numbers are executed according to unique rules defined in such a way that they carry uncertainty rather than producing a single definite result, as in classical mathematics. Basic fuzzy arithmetic operations for triangular fuzzy numbers are as follows: (Toptancı & Aktaş Potur, 2021: 108):

$$\tilde{A}_1 = (l_1, m_1, u_1) \quad \tilde{A}_2 = (l_2, m_2, u_2) \tag{1}$$

$$\tilde{A}_1 + \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

$$\tilde{A}_1 - \tilde{A}_2 = (l_1 - u_2, m_1 - m_2, u_1 + l_2) \tag{3}$$

$$\tilde{A}_1 \times \tilde{A}_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \tag{4}$$

$$\tilde{A}_1 / \tilde{A}_2 = (l_1 / u_2, m_1 / m_2, u_1 / l_2) \tag{5}$$

$$\lambda \times \tilde{A}_1 = (\lambda \times l_1, \lambda \times m_1, \lambda \times u_1) \tag{6}$$

In this study, AI risks in PPC processes were assessed by integrating triangular fuzzy numbers into the conventional FMEA procedure. In this context, the O, S, and D parameters were used on a five-level linguistic scale: very low (VL), low (L), medium (M), high (H), and very high (VH). The applicability of this scale for FMEA was previously demonstrated by Dağsuyu et al. (2016). The corresponding triangular fuzzy number set, presented in Table 1, was used to convert experts' linguistic assessments into fuzzy ratings for subsequent computations.

Table 1: Fuzzy Scale for Occurrence, Severity, and Detectability

Occurrence (O)		Severity (S)		Detectability (D)	
Defining	Fuzzy number	Defining	Fuzzy number	Defining	Fuzzy number
Very low	(0, 1, 3)	Very low	(0, 1, 3)	Very low	(7, 9, 10)
Low	(1, 3, 5)	Low	(1, 3, 5)	Low	(5, 7, 9)
Medium	(3, 5, 7)	Medium	(3, 5, 7)	Medium	(3, 5, 7)
High	(5, 7, 9)	High	(5, 7, 9)	High	(1, 3, 5)
Very high	(7, 9, 10)	Very high	(7, 9, 10)	Very high	(0, 1, 3)

Source: Dağsuyu et al. (2016:291)

As shown in Table 1, the Detectability scale is ranked in reverse order. The main reason is that as it becomes more difficult to detect a problem in advance, the risk increases, and this increase must be reflected in the assessment in a way that contributes more to the RPN value. In the adopted approach, the O, S, and D parameters for each risk are represented as fuzzy numbers $(\tilde{O}, \tilde{S}, \tilde{D})$ derived from linguistic evaluations, thereby incorporating uncertainties in expert judgments into the model and enabling calculations as in the fuzzy RPN (\widetilde{RPN}) Equation (7).

$$\widetilde{RPN} = \tilde{O} \times \tilde{S} \times \tilde{D} \tag{7}$$

As a result of fuzzy arithmetic operations, a triangular fuzzy RPN value is obtained for each risk. However, to rank risks based on comparable individual scores, these fuzzy RPN values must be defuzzified. Although different defuzzification approaches exist in the literature, one of the most commonly used methods in practice is the centre of gravity (COG) approach. The process of this approach is presented in Equation 8 (Testik & Tok Unlu, 2023: 578).

$$COG = \frac{l + m + u}{3} \tag{8}$$

Risks related to the use of artificial intelligence in PPC processes

AI applications enhance PPC processes by increasing flexibility and responsiveness in demand forecasting, production planning, capacity utilisation, and performance monitoring. However, these tools also introduce specific risks. As production systems generate greater volumes and varieties of data, challenges related to data collection, cleaning, standardisation, and access become more pronounced (Mäule & Götte, 2025, p. 1256). The effectiveness of AI in PPC depends on the availability of clean, large-scale data, making data-related issues the primary risks associated with AI-supported tools in these processes. Additionally, evolving field conditions alter data flows, which can cause AI models to become misaligned over time and reduce output quality (Fries et al., 2025, p. 294).

Data challenges extend beyond issues of accuracy and completeness. Increasing data diversity and the integration of information from multiple systems heighten the need for interoperability, while the absence of standardised data structures complicates communication between systems. Combined with the inherent complexity of PPC tasks, technical compatibility issues, and the risk of operational disruptions, integrating new data-driven solutions with existing equipment and infrastructure can be difficult (Mäule & Götte, 2025, p. 1256). Additionally, because PPC processes are closely linked to human decision-making, explainability is essential. The practical acceptance of AI-supported PPC recommendations depends on users' ability to interpret outputs and assess their reliability. As models generate varying outcomes with continuous data updates, this may conflict with users' expectations for decision stability, potentially leading to resistance or withdrawal even when the system functions as intended (Fries et al., 2025, p. 299).

In addition, AI applications must operate in an integrated manner. The need for AI applications to integrate with existing MRP and MES introduces additional risks related to system integration and operational continuity. Non-standardised data structures and system incompatibilities can disrupt data flows and cause inconsistencies in planning outputs. Security, bias, and governance represent further categories of risk associated with AI use in PPC. As AI systems require increasing amounts of data, concerns regarding data privacy and cybersecurity become more significant, with unauthorised access or data manipulation potentially resulting in severe operational consequences (Guo & Li, 2024, pp. 72-73). Additionally, models may reproduce historical data imbalances, increasing the risk of algorithmic bias that systematically affects decision-making rather than manifesting as isolated errors.

Risks associated with artificial intelligence in PPC can vary significantly depending on the application context, data ecosystem, and system maturity. Since PPC decisions progress through interdependent

stages such as demand forecasting, material and capacity planning, scheduling and dispatching, and shop-floor control, disruptions related to AI usage often go beyond a single technical issue. They can spread throughout the process, affecting plan accuracy, plan stability, and execution performance. To clarify the evaluation framework, this study compiled prominent risks identified in the literature into a structured risk list. To distinguish clearly between risk identification and risk assessment, a sequential approach was adopted. Initially, a literature-based risk pool was created and refined to a concise set of recurring risks in AI-enabled PPC discussions. This preliminary list was presented to experts solely for validation of scope and wording, ensuring each risk was relevant to PPC practice and articulated for consistent interpretation by practitioners. The objective of this step was not to introduce new risk domains during the evaluation phase, but to refine definitions, eliminate redundancies, and ensure content validity. Likewise, the assessment process took place after the risk set was finalised. The risk list in question is presented in Table 3.

Table 2: Risk Considered in the Study and Their Codes

Risks	Scope	Sources	Code
Data quality risk	Reduced reliability of output due to inaccurate, incomplete, or inconsistent data.	Kunecová et al. (2025), Mäule and Götte (2025), Guo and Li (2024), Sinha and Lee (2024), Mao et al. (2019)	R1
Model alignment and currency risk	Loss of model validity and performance as operating conditions and data streams change over time.	Mäule and Götte (2025), Gabsi (2024), Sinha and Lee (2024), Wan et al. (2021)	R2
Lack of explainability risk	Inability of users to understand, interpret, or trace the rationale behind model outputs.	Fries et al. (2025), Gabsi (2024), Guo and Li (2024), Vyhmeister et al. (2023), Wan et al. (2021)	R3
Cybersecurity risk	System exposure to unauthorised access, data manipulation, or cyberattacks.	Sinha and Lee (2024), Gabsi (2024), Laska and Karwala (2023), Bécue et al. (2021), Wan et al. (2021)	R4
System integration risk	Technical or semantic incompatibilities with existing systems (e.g., MRP/MES) that disrupt data flow.	Fries et al. (2025), Mäule and Götte (2025), Sinha and Lee (2024), Roblek et al. (2024)	R5
User adoption and competency mismatch risk	Reduced effectiveness due to insufficient user acceptance or inadequate user capabilities.	Fries et al. (2025), Godinho Filho et al. (2025), Kunecová et al. (2025), Gabsi (2024), Sinha and Lee (2024), Roblek et al. (2024)	R6
Operational continuity risk	Process disruptions caused by system downtime, infrastructure failures, or over-reliance on AI.	Mäule and Götte (2025), Sinha and Lee (2024), Bécue et al. (2021), Wan et al. (2021), Mao et al. (2019)	R7
Algorithmic bias risk	Systematic reflection of imbalances in historical data within decisions or recommendations.	Gabsi (2024), Guo and Li (2024), Sinha and Lee (2024), Vyhmeister et al. (2023)	R8
Ethical and compliance risk	Conflicts with ethical principles, regulatory requirements, or organisational policies.	Godinho Filho et al. (2025), Gabsi (2024), Guo and Li (2024), Laska and Karwala (2023), Vyhmeister et al. (2023), Wan et al. (2021)	R9

The scope of risks examined in this study was intentionally aligned with the ongoing digital transformation of PPC processes, where AI is increasingly integrated across business functions. Accordingly, the risks analysed were selected based on the most prominent issues identified in the existing literature on AI adoption. By focusing on these widely recognised risk dimensions, the study seeks to establish a structured, manageable framework that enables a more controlled, informed transition to AI-supported PPC processes.

Study group

The study group comprised academics researching PPC, who were selected through purposive sampling. This approach allows data to be obtained from knowledge-rich cases with high levels of information and experience relevant to the research question (Palinkas et al., 2015, p. 534). Although AI has rapidly gained popularity in recent years, its use in PPC processes in Turkey is still in the early stages of maturation, and a standard/common application framework has not yet emerged across

sectors. Under these conditions, field participants' assessments will mostly be based on their experiences with specific tools, suppliers, and setups used in their organisations. This situation carries the risk of reducing the study's overall objective to tool or organisation-dependent judgments and of producing misleading results. Since the study aims to develop a general risk/prioritisation framework for AI-based PPC rather than defining a specific application, PPC researchers capable of interpreting different application contexts through literature and theoretical knowledge were considered suitable data providers. This preference enhances conceptual consistency by reducing tool-dependent bias in early maturity conditions. In this context, potential participants were identified via the Council of Higher Education's (YÖK) Academic Database by filtering for the PPC field, and those meeting the inclusion criteria were invited by email. Data were collected online between November 25 and December 9, 2025. Fourteen faculty members from various universities consented to participate. Each participant completed the evaluations independently online, drawing on their academic expertise. To ensure participant confidentiality, each participant has been assigned an anonymous code ranging from P1 to P14.

Procedural flow of the study

The study followed a structured procedure flow. First, risks associated with the use of AI in PPC processes were identified through a comprehensive literature review and validated by expert opinion. Second, a fuzzy FMEA framework was created by defining linguistic variables for the O, S, and D parameters and corresponding triangular fuzzy numbers. Third, expert assessments were collected online from the working group. Finally, risks were analysed in accordance with the adopted methodology.

Ethical considerations

This study was conducted based on the approval of the Alanya Alaaddin Keykubat University Social and Humanities Scientific Research and Publication Ethics Committee, dated 12.11.2025, and numbered 10/16. All stages of the research were carried out in accordance with the principles and standards of scientific research and publication ethics. Participants voluntarily participated in the study; they were informed about the purpose and scope of the research, and their informed consent was obtained electronically before data collection. Participants' identity information was kept confidential, and the data were anonymised and used solely for scientific purposes. The study's scientific content was created entirely by the author. Only for translation processes and grammar-writing revisions, Grammarly, a generative artificial intelligence application that supports grammatical accuracy, spelling, and stylistic consistency in texts, was used. This tool made no intellectual or analytical contribution to the study.

Analysis and findings

The analysis phase of the study was conducted in accordance with the "Procedural Flow of the Study" and ensured traceability of each step. In this regard, it was first verified that each participant met the study group inclusion criteria, and all participants did. Subsequently, the linguistic assessments of each participant for the O, S, and D risk parameters were compiled to create an assessment matrix. This matrix is presented in Table 4.

Table 4: Participants' Assessments of Risks

P	R1			R2			R3			R4			R5			R6			R7			R8			R9		
	O	S	D	O	S	D	O	S	D	O	S	D	O	S	D	O	S	D	O	S	D	O	S	D	O	S	D
P1	L	H	VH	H	VH	H	L	H	H	VH	VH	H	H	H	H	VH	M	H	L	M	H	VL	H	H	L	H	VH
P2	L	H	H	M	H	M	H	VH	H	H	M	M	L	H	H	H	H	H	H	H	L	H	H	L	H	H	M
P3	L	VH	L	H	H	H	H	H	L	H	H	H	L	L	H	H	H	M	H	H	H	M	M	H	H	H	M
P4	H	VH	M	H	VH	M	H	H	M	H	VH	L	H	H	M	M	H	M	H	H	M	M	M	M	M	H	M
P5	H	H	M	L	M	H	M	H	H	M	VH	M	L	H	M	H	H	H	H	H	M	H	H	M	H	H	M
P6	H	H	H	L	L	H	H	H	VH	M	VH	H	L	VL	H	H	VH	L	H	M	H	H	H	L	L	L	L
P7	M	M	VL	VL	VL	L	L	H	L	VH	VH	M	VL	L	H	VH	VH	M	L	VH	M	VH	VH	L	H	H	M
P8	L	H	L	M	H	M	M	M	L	H	VH	M	M	M	L	L	H	L	L	L	H	M	M	L	L	M	M
P9	M	H	L	H	H	L	H	H	M	H	H	M	H	H	H	H	H	H	H	H	H	M	M	M	L	H	H
P10	M	H	M	M	H	H	H	H	H	M	H	M	M	H	H	M	H	H	H	H	H	H	H	H	M	H	H
P11	M	L	M	L	L	M	H	H	H	M	H	M	L	M	M	H	H	VH	M	M	H	M	H	VH	M	M	H
P12	L	L	H	L	L	H	M	M	H	M	H	M	L	L	M	H	H	M	L	L	M	L	L	M	H	H	L
P13	M	M	L	VH	H	H	H	H	L	H	VH	L	M	M	H	VH	VH	VH	L	L	L	VH	VH	L	VH	VH	M
P14	M	H	M	M	H	M	H	H	L	H	H	M	H	H	H	H	H	H	H	H	H	M	H	M	M	M	M

*P= Participant

Table 4 presents the raw data collected in the study. These data were subsequently converted into triangular fuzzy numbers using the established methodology, yielding a fuzzy assessment matrix. This approach enabled the consistent mathematical representation of participants' linguistic judgments. The resulting fuzzy evaluation matrix is shown in Table 5.

Table 5: Participants' Fuzzy Evaluation of Risks

P	R1			R2			R3		
	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}
P1	(1, 3, 5)	(5, 7, 9)	(0, 1, 3)	(5, 7, 9)	(7, 9, 10)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
P2	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(1, 3, 5)
P3	(1, 3, 5)	(7, 9, 10)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
P4	(5, 7, 9)	(7, 9, 10)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P5	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)
P6	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(0, 1, 3)
P7	(3, 5, 7)	(3, 5, 7)	(7, 9, 10)	(0, 1, 3)	(0, 1, 3)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)
P8	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)
P9	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P10	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P11	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P12	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)
P13	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
P14	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
P	R4			R5			R6		
	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}
P1	(7, 9, 10)	(7, 9, 10)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(7, 9, 10)	(3, 5, 7)	(1, 3, 5)
P2	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P3	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P4	(5, 7, 9)	(7, 9, 10)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)
P5	(3, 5, 7)	(7, 9, 10)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P6	(3, 5, 7)	(7, 9, 10)	(1, 3, 5)	(1, 3, 5)	(0, 1, 3)	(1, 3, 5)	(5, 7, 9)	(7, 9, 10)	(5, 7, 9)
P7	(7, 9, 10)	(7, 9, 10)	(3, 5, 7)	(0, 1, 3)	(1, 3, 5)	(1, 3, 5)	(7, 9, 10)	(7, 9, 10)	(3, 5, 7)
P8	(5, 7, 9)	(7, 9, 10)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)
P9	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P10	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)
P11	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(0, 1, 3)
P12	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P13	(5, 7, 9)	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(7, 9, 10)	(7, 9, 10)	(0, 1, 3)
P14	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
P	R7			R8			R9		
	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}	\bar{O}	\bar{S}	\bar{D}
P1	(1, 3, 5)	(3, 5, 7)	(1, 3, 5)	(0, 1, 3)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(0, 1, 3)
P2	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P3	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P4	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)
P5	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P6	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)
P7	(1, 3, 5)	(7, 9, 10)	(3, 5, 7)	(7, 9, 10)	(7, 9, 10)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
P8	(1, 3, 5)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)
P9	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(5, 7, 9)	(1, 3, 5)
P10	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(1, 3, 5)
P11	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(0, 1, 3)	(3, 5, 7)	(3, 5, 7)	(1, 3, 5)
P12	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(1, 3, 5)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
P13	(1, 3, 5)	(1, 3, 5)	(5, 7, 9)	(7, 9, 10)	(7, 9, 10)	(5, 7, 9)	(7, 9, 10)	(7, 9, 10)	(3, 5, 7)
P14	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)

The data in Table 5 show the values converted to triangular fuzzy numbers for each participant's linguistic assessments of the \tilde{O} , \tilde{S} , and \tilde{D} risk parameters. To combine all participants' opinions into a common assessment, the fuzzy assessments for each participant regarding the O, S, and D parameters for each risk were aggregated to obtain a single consensus fuzzy value per risk. In this process, the arithmetic mean was used to ensure that participants' opinions were given equal weight. Subsequently, \overline{RPN} values for each risk were calculated using Equation (7). Subsequently, these \overline{RPN} values were clarified using the centre-of-gravity method. Equation (8) was used for this process. The findings from these processes are presented in Table 6.

Table 6: Risk Assessment Results

Risks	\tilde{O}	\tilde{S}	\tilde{D}	\overline{RPN}	Defuzzified RPN
R1	(2.71, 4.71, 6.71)	(4.43, 6.43, 8.29)	(3.21, 5.14, 7.07)	(38.64, 155.86, 393.40)	195.97
R2	(3.07, 5.00, 6.93)	(3.93, 5.86, 7.71)	(2.29, 4.29, 6.29)	(27.58, 125.51, 335.97)	163.02
R3	(4.86, 6.86, 8.79)	(4.86, 6.86, 8.79)	(2.64, 4.57, 6.57)	(51.35, 188.08, 461.88)	233.77
R4	(4.57, 6.57, 8.43)	(5.86, 7.86, 9.36)	(2.86, 4.86, 6.86)	(76.50, 250.79, 540.80)	289.36
R5	(2.50, 4.43, 6.43)	(3.36, 5.29, 7.29)	(1.71, 3.71, 5.71)	(14.39, 86.94, 267.64)	122.99
R6	(4.86, 6.86, 8.64)	(5.00, 7.00, 8.79)	(1.71, 3.57, 5.57)	(41.63, 171.43, 423.06)	212.04
R7	(3.43, 5.43, 7.43)	(3.86, 5.86, 7.79)	(2.14, 4.14, 6.14)	(28.34, 131.73, 355.28)	171.78
R8	(3.79, 5.71, 7.57)	(4.43, 6.43, 8.29)	(3.07, 5.00, 7.00)	(51.49, 183.67, 439.14)	224.77
R9	(3.43, 5.43, 7.36)	(4.43, 6.43, 8.36)	(2.64, 4.57, 6.57)	(40.13, 159.53, 404.04)	201.23

Table 6 indicates that risks related to AI usage in PPC are not concentrated around a single technical issue but rather form a multidimensional risk architecture across the axes of security, human factors, and operational continuity. Indeed, the defuzzified RPN values range from 122.99 to 289.36, indicating a clear ranking in risk priority. Meanwhile, the assessment conducted using triangular fuzzy numbers preserves the uncertainty in expert judgments throughout the calculation chain. Therefore, the findings not only produce a ranking but also reveal the criticality dynamics of each risk in a traceable manner through the O, S, and D components.

The analysis results clearly produce a three-level view. At the top level, cybersecurity risk (R4) ranks first with 289.36, followed by lack of explainability risk (R3) with 233.77 and algorithmic bias risk (R8) with 224.77. The common denominator of these three risks is that, given the decision-intensive nature of PPC, reliability and controllability dimensions are decisive before AI performance. This determinism is particularly evident in the severity component of R4. Indeed, since cybersecurity is an adversarial/intentional threat class targeting not only information assets but also the integrity of the PPC decision flow, the high central value of the \tilde{S} profile is the main driver of the Fuzzy RPN. The critical point here is that R4 not only has a high priority score but also has the potential to become a systemic vulnerability in the PPC context, moving beyond a single error, given its capacity to produce sudden, cascading effects on decision quality and operational execution. The positioning of R3 and R8 at the top indicates that a significant portion of AI risks in PPC is shaped more by epistemic risks (the inability to trace the model's cause-and-effect logic and the embedding of bias in the decision-making mechanism) than by model accuracy. The high \tilde{O} and \tilde{S} center values for R3 suggest that lack of explainability is perceived not as an exceptional situation in daily PPC practices, but as a recurring oversight bottleneck. In R8, the notable point is the relatively high detectability dimension. Since bias is often not a visible failure but a mechanism that gradually reflects in decision outputs, the character of delayed detection in risk escalation becomes apparent. This picture provides strong insight into the need to address AI governance in PPC, not only through technical performance metrics but also through traceability, fairness, and the capacity to justify decisions.

At the second level, User adoption and competency mismatch (R6) with 212.04, Ethical and compliance risk (R9) with 201.23, and Data quality risk (R1) with 195.97 are clustered. This cluster suggests that the risk profile is also closely related to organisational placement and data infrastructure. In R6, the \tilde{O} and \tilde{S} components are high, while the \tilde{D} center value is relatively lower. In other words, participants imply that this risk is not entirely visible but remains a high priority because it could drag down PPC performance. In other words, the criticality of R6 stems not so much from its inability to be captured, but rather from the perception that, even if captured, it is difficult to mitigate for organisational reasons. The high ranking of R9 indicates that the ethical-principled and regulatory compliance axis in corporate decision-making processes, such as PPC, is no longer a secondary issue, but is now considered a component that directly determines the risk agenda. The relatively high priority of R1 points to a scenario where data quality issues can cause silent degradation in AI usage in PPC, thereby increasing

the detectability component. This is because incorrect or incomplete data reduces the reliability of outputs, while the problem's root cause is often only understood after it has been reflected in the decision outputs.

At the lower level, Operational continuity (R7) with 171.78, Model compliance and currency (R2) with 163.02, and System integration (R5) with 122.99. The fact that these risks are ranked lower does not mean that they are insignificant. Rather, it indicates that experts assume relatively more manageable control mechanisms in these areas or believe that the effects are more limited. In particular, the relatively low ranking of R2 indicates that, although model drift/obsolescence is a critical problem in PPC, evaluators either see it as compensable through operational practices or consider its impact less direct than that of systemic risks such as security/traceability. The fact that R5 ranks lowest in priority suggests that integration risk is perceived as a one-off project-implementation problem. However, there is an important nuance: R5 has a relatively wide fuzzy RPN spread. That is, fuzzy RPN values have a wide range. This suggests heterogeneity in participant opinions and that integration could become critical in certain contexts. Therefore, the lower ranks should be interpreted as a call for clearer definitions of the contextual conditions (enterprise architecture, MRP/MES maturity, data integration architecture) rather than as an area that can be disregarded in terms of risk.

Discussion, conclusion, and recommendations

This study systematically assessed the risks associated with AI use in PPC processes by adopting a fuzzy FMEA framework that explicitly accounts for uncertainty in expert judgments. By structuring the analysis around the dimensions of occurrence frequency, severity, and detectability, and by converting linguistic expert assessments into defuzzified RPN values, the study contributes to a topic that is extremely under-represented in the existing literature on AI risks in PPC.

The findings indicate that the risks associated with AI implementation in PPC constitute a multifaceted profile encompassing security, human factors, and operational continuity. Indeed, the defuzzified RPN values range from 122.99 to 289.36, indicating a clear differentiation in risk priority. In this context, the priority ranking of risks is as follows: R4 Cybersecurity (289.36) > R3 Lack of explainability (233.77) > R8 Algorithmic bias (224.77) > R6 User adoption and competency mismatch (212.04) > R9 Ethics and compliance (201.23) > R1 Data quality (195.97) > R7 Operational continuity (171.78) > R2 Model alignment and currency (163.02) > R5 System integration (122.99). This result suggests that cybersecurity is not solely an information technology issue but also a factor that can directly compromise the reliability of planning outcomes if AI models or data flows are breached. In these contexts, unauthorised access or data manipulation can influence planning and scheduling decisions, thereby assessing the perceived severity of cybersecurity risks. This inference aligns with Mäule and Götte (2025), who identify cybersecurity and data protection as primary barriers to the adoption of data-driven PPC systems, emphasising that unresolved security challenges can impede sustainable implementation. Laska and Karwala (2023) similarly note that AI applications in industrial settings introduce new operational and governance risks in the absence of robust control mechanisms, reinforcing the perspective that security vulnerabilities may have implications beyond technical concerns. The emphasis on data quality and model alignment or currency primarily risks positioning it as a sustainability issue affecting AI performance over time, rather than as a singular implementation challenge. In other words, the critical threat is not that the model will be wrong once, but that it will quietly become less valid as routings, constraints, and shop-floor conditions change, while the organisation continues to use it as if nothing has changed. This inference aligns with Mäule and Götte (2025), who identify data-related issues and operational constraints as persistent barriers to data-driven PPC. It also corresponds with the findings of Usuga Cadavid et al. (2020), who emphasise the challenges of maintaining up-to-date ML-supported PPC models in dynamic manufacturing environments. The importance of explainability demonstrates that risks associated with AI in PPC are understood as socio-technical risks: even if an algorithm performs well statistically, if planners cannot interpret, justify, or question the algorithm's recommendations under time pressure and disruptions, the algorithm may still be considered risky. This means that explainability functions as a control and accountability condition for the adoption of AI in planning, rather than as a nice-to-have interface feature. This idea is supported by Fries et al. (2025), who show that production planning is inherently collaborative and negotiation-focused, and that the practical applicability of AI support depends on how well it can be integrated into employees' decision-making practices and responsibilities. Finally, the high ranking of algorithmic bias indicates that respondents interpret AI risk as the potential for AI systems to systematically establish and scale problematic decision patterns by learning from past data. Practically speaking, bias is not seen as an occasional mistake but as a mechanism that can institutionalise unfair or inefficient priorities within planning routines (e.g., by repeatedly favouring specific orders, lines, or parameter selections). Laska

and Karwala (2023) underscore that the adoption of AI brings not only opportunities but also governance-related risks that can affect organisational performance and accountability if not explicitly managed, laying the groundwork for this conclusion. Meanwhile, system integration has been assessed as relatively low risk; however, this finding should not be interpreted as insignificant. On the contrary, this assessment shows that participants view system integration challenges as more manageable and technically resolvable. The relatively lower risk rating reflects an expectation that integration risks can be mitigated through the use of standards, interfaces, and phased implementation strategies. Nonetheless, if system integration failures adversely affect data flow, traceability, or the distribution of responsibilities, they may indirectly trigger higher-priority risks, including data quality, explainability, and model currency. Therefore, system integration should be considered not as an isolated threat but as a supporting risk factor that shapes the emergence and intensification of other risks.

The study's results yield several practical recommendations for organisations aiming to implement AI in PPC effectively. First, cybersecurity must be regarded as a foundational requirement in the development of these systems, rather than a secondary technical consideration. Indeed, a narrow focus on network security or software updates may expose significant risks. For example, focusing solely on network security or software updates can lead to hazardous consequences. Therefore, issues such as data access, authorisation, traceability, and auditability should be considered cornerstones of the design before initiating the transition to AI systems. Furthermore, it should not remain merely a policy document for responding to a potential cyber incident; it is crucial to develop a proactive strategy outlining the course of action to be taken when data flow is interrupted, anomalies are detected, or suspicion arises that the model has been manipulated. In this regard, model performance monitoring should be supported with explicit drift indicators and predefined triggers for revalidation, such as new product introductions, routing revisions, equipment changes, persistent deviations between planned and realised times, or major demand and supply disruptions. Additionally, organisations should establish procedures for when a model should be retrained or temporarily disabled to prevent legacy models from continuing to influence planning decisions by default, and clearly define the steps involved in these processes. For instance, concise rationale indicators that summarise the variables influencing recommendations, sensitivity cues that reflect the impact of minor changes, and uncertainty signals can help planners calibrate their confidence. The most critical factor in improving explainability, however, is the systematic collection of user feedback and the creation of a feedback loop that allows planners to invalidate model proposals when necessary. These interventions should be documented and incorporated into the learning process. Finally, integration and operational sustainability may appear to be low priorities, but they can be critical risks that trigger higher risks. Therefore, integration and continuity plans should be monitored along with contextual triggers.

From a methodological perspective, this study makes a valuable contribution to the literature by addressing the risks associated with AI tools in PPC processes within a framework that accounts for uncertainty and supports structured prioritisation. However, the study has some limitations. First, the assessment is based on expert judgments from academics specialising in PPC, which may limit generalizability across industries with different maturity levels. This limits the direct generalisation of the results to all sectors or businesses with different levels of application maturity. Furthermore, although the set of risks addressed in the study was determined through a literature review and expert opinions, contextual factors such as supply chain dependencies, reliance on external software providers, and regulatory requirements were not examined in detail. Therefore, the relative importance of certain risk types may vary across specific industries or organisational structures. Furthermore, the study treats risks as independent elements and does not model causal relationships or interactions between them. In practice, risks such as data quality, model timeliness, and explainability can exhibit a dynamic structure in which they trigger one another. Excluding these interactions may prevent the combined effects of risks from being fully reflected.

Finally, the proposed approach presents a conceptual, evaluation-based framework and has not been validated over the long term through real-world industrial applications. This limits the extent to which conclusions can be drawn regarding how risk priorities, detection capability, and mitigation effectiveness evolve once AI in PPC is implemented on the shop floor. Future research should conduct longitudinal, multi-site case studies across varied production settings (e.g., make-to-order versus make-to-stock; SMEs versus large firms) and test the stability of risk rankings under demand shifts, process changes, and model drift. In addition, comparative studies should benchmark the proposed prioritisation outcomes against alternative risk assessment approaches and human planners' decisions to assess practical usefulness, calibration quality, and decision impact. To strengthen the relevance of implementation, future studies should operationalise data governance, monitoring, and retraining routines, as well as cybersecurity-by-design, as testable constructs, and evaluate their effects on

measurable risk-reduction outcomes. Moreover, the framework should be extended with human-in-the-loop and explainability requirements to reflect how planners and operators use, override, and learn from AI recommendations in day-to-day PPC practices. Methodologically, integrating simulation or digital-twin experiments with empirical data can help stress-test rare disruption scenarios, including breakdowns or material shortages, and analyse the dynamic interactions among risk clusters.

Peer-review:

Externally peer-reviewed.

Conflict of interests:

The author declares no conflict of interest.

Grant Support:

The author declares that this research received no external funding.

Acknowledgement:

I sincerely thank the handling editor and the anonymous reviewers for their constructive comments, which helped improve the manuscript.

Ethics Committee Approval:

Ethics committee approval for this study was received from the Social and Humanities Scientific Research and Publication Ethics Committee at Alanya Alaaddin Keykubat University on 12/11/2025, document number 10/16.

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