Proceedings of the 16th International Conference on Industrial Engineering and Operations Management
Ankara, Türkiye, June 23-25, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AN16.20260056
Published: June 23, 2026

Towards SPC 5.0: Synthesizing Industry 5.0 Principles and SPC Design into an Integrated Framework and Research Agenda

Ali Baştaş
Assistant Professor, Industrial Engineering
Department of Industrial Engineering
Eastern Mediterranean University
99628, Famagusta, North Cyprus via Mersin 10, Türkiye
Ali.bastas@emu.edu.tr

Abstract

Industry 5.0 is increasingly shifting manufacturing priorities towards human-centricity, sustainability, and resilience, challenging the conventional assumptions embedded in Statistical Process Control (SPC) design and deployment. This study develops an integrated perspective of SPC 5.0 by first conducting a synthesizing review that consolidates core Industry 5.0 principles and examines them against established SPC design principles. Building on this synthesis, SPC design principles are revisited with a view to laying the foundations of an SPC 5.0 framework that extends SPC from a purely statistical monitoring mechanism to a socio-technical quality control capability. For demonstration of the formulated design principles and associated artifact, an illustrative worked example is considered, introducing a representative process monitoring scenario to the framework, and showing how chart design choices, escalation logic, and human–AI decision support can be aligned with Industry 5.0 requirements without compromising statistical rigor. The resulting SPC 5.0 perspective is positioned explicitly as an extension of, Quality 4.0 and smart SPC, inheriting their digital and analytical foundations while elevating human-centricity, sustainability, and resilience to first-class design requirements. Finally, a future research agenda outlining testable propositions and implementation challenges is discussed including measurement of human-centric performance, trust and accountability in augmented SPC, and validation pathways across manufacturing and service contexts.

Keywords
Industry 5.0; Statistical process control; Human-in-the-loop quality; SPC 5.0 framework; Resilient and sustainable manufacturing.

1. Introduction
Statistical Process Control (SPC) remains a foundational method for achieving process stability and managing variation through disciplined signal detection and reaction planning. Classic SPC logic distinguishes common-cause from special-cause variation and translates process data into timely containment and corrective action using validated chart design, rational subgrouping, and run rules (Montgomery 2020; Mitra 2021; Nelson 1984).

Industry 4.0 has expanded the data and connectivity landscape in which SPC operates through cyber-physical integration, pervasive sensing, and real-time information flows, enabling data-rich monitoring architectures and quicker feedback loops (Lasi et al. 2014; Zhong et al. 2017; Xu et al. 2018). However, Quality 4.0 research repeatedly highlights that digital enablement does not automatically translate into quality improvement: organizations struggle with data readiness, project selection, capability gaps, and sustaining analytics initiatives at scale (Sony et al. 2020; Escobar et al. 2021; Sader et al. 2022; Zonnenshain and Kenett 2020; Antony et al. 2023).

In practical industrial settings, this gap manifests in concrete and increasingly costly ways. High-frequency, sensor-dense monitoring can overwhelm operators with alarms, producing alarm fatigue and eroding disciplined reaction (Antony et al. 2023). Opaque, machine learning (ML) generated alerts that cannot be explained at the line undermine operator trust and accountability, leaving signals unactioned. Resource intensity losses, such as rising energy and material consumption per conforming unit, frequently accumulate invisibly because conventional conformance-only charts do not monitor them. The same connectivity that enables data-rich SPC also exposes measurement and feature pipelines to sensor drift, data quality failures, and cyber-physical manipulation, any of which can silently invalidate control limits. These phenomena indicate that the binding constraint is no longer the availability of data or analytics, but the absence of a design logic that keeps statistically valid monitoring interpretable, sustainability aware, and resilient under real operating conditions. At the same time, learning-based and intelligent monitoring methods are maturing rapidly and offer clear potential to augment classical charting with predictive and diagnostic capability, provided they remain governed and accountable (Apsemidis et al. 2020; Tran et al. 2022; Escobar et al. 2025).

Industry 5.0 has been positioned by the European Commission as a complementary orientation to Industry 4.0 that emphasizes human-centricity, sustainability, and resilience as emerging design imperatives for industrial systems (Breque et al. 2021; van Erp et al. 2024). This shift challenges the implicit assumptions underlying conventional SPC, particularly the tendency to treat it as a purely statistical tool detached from socio-technical design, accountability, and multi-objective performance considerations spanning quality, sustainability, and resilience. Ultimately, the guiding research question of this study emerged as:

How should SPC design principles be revisited to embed the Industry 5.0 pillars (human-centricity, sustainability, and resilience) into SPC design and deployment while preserving statistical validity and disciplined reaction planning?

Accordingly, this paper develops an integrated perspective of SPC 5.0 where statistical rigor is preserved but embedded within (i) role-aware, human-in-the-loop escalation and learning, (ii) sustainability-augmented critical-to-quality characteristics (CTQCs), and (iii) resilience-by-design in data pipelines and governance. The contribution is an SPC 5.0 framework, and a set of design principles grounded in extant SPC and Quality 4.0/Industry 4.0 literature, with an illustrative worked example demonstrating feasibility of aligned chart design and escalation logic. SPC 5.0 is conceived here as an extension of the governed, connected, and workflow-closed SPC capability associated with Industry 4.0 and Quality 4.0, while making human-centricity, sustainability, and resilience explicit design requirements.

1.1 Objectives

In line with the above agenda, research objectives of this conference paper were set to:

- Consolidate core Industry 5.0 principles and examine their implications for conventional SPC design and deployment.
- Synthesize a set of SPC 5.0 design principles and propose an integrated framework spanning data, analytics, governance, and learning layers.
- Demonstrate the framework through an illustrative worked example that aligns chart design, escalation logic, and human–AI decision support.
- Outline a research agenda with testable propositions for future empirical validation across manufacturing and service contexts.

2. Literature Review

Industry 4.0 research characterizes smart factories as cyber-physical environments where physical processes are connected to networked devices, data services, and real-time analytics (Lasi et al. 2014; Zhong et al. 2017; Xu et al. 2018). In parallel, Quality 4.0 literature positions digitalization, big data, and artificial intelligence (AI) as enablers for new quality management capabilities across the value chain, while noting implementation constraints related to data, culture, and capability readiness (Sony et al. 2020; Sader et al. 2022; Zonnenshain and Kenett 2020). A recent empirical study of organizational readiness further highlighted that leadership, culture, and top management commitment are critical for successful Quality 4.0 adoption (Antony et al. 2023). Within Quality 4.0, several contributions focused specifically on process monitoring and SPC evolution. Escobar et al. (2021) reviewed big data challenges and identified recurring implementation gaps including paradigm misfit, project selection failures, and relearning problems. More recently, Escobar et al. (2025) proposed Learning Quality Control as an evolution of SPC that uses machine learning classifiers for proactive defect prediction, while stressing that the new capabilities should be anchored in statistical and managerial foundations.

On the SPC implementation side, recent studies have proposed guidelines and architectures to integrate conventional SPC into Industry 4.0 systems. Goecks et al. (2024) developed guidelines for transforming SPC into smart SPC, emphasizing real-time data collection, integration with industrial internet of things (IIoT) ecosystems, and predictive capabilities. Dutta et al. (2021) investigated digitalization priorities for quality control in SMEs, advocating holistic digitalization of quality processes across the Plan-Do-Check-Act (PDCA) cycle to avoid disparities between paper-based practices and digital value chains. Alongside digitalization, methodological and foundational SPC issues still maintain their relevance, such as robustness to non-normality and the need for appropriate run rules for special cause detection (Schoonhoven and Does 2010; Nelson 1984). These considerations remain highly applicable, as the high-frequency and high-dimensional data implied by Quality 4.0 capabilities do not eliminate the need for rational subgrouping, stable measurement systems, and disciplined reaction plans (Montgomery 2020; Mitra 2021). In this sense, SPC 5.0 does not replace the architectural and governance logic emerging from smart SPC and SPC 4.0 work; rather, it builds on that logic and reinterprets it through the Industry 5.0 pillars.

Industry 5.0 is emerging to add a distinct lens to this evolving landscape. The European Commission articulated Industry 5.0 around the three pillars of human-centricity, sustainability, and resilience (Breque et al. 2021). Recent scholarly work further consolidated Industry 5.0 as a strategic orientation that explicitly integrates human-centricity, sustainability, and resilience as co-equal design parameters for industrial value creation (van Erp et al. 2024). Antomarioni et al. (2025), in one of the early works on the emerging area of Quality 5.0, explicitly argued that human expertise and contextual judgment should remain central in real-time quality monitoring and predictive analytics environments. While Quality 4.0 and smart SPC literature has begun to address technology, data, and organizational readiness, fewer works have explicitly translated Industry 5.0 pillars into SPC design requirements. This gap motivated the synthesis undertaken in this study towards SPC 5.0. The corresponding scarcity of real-world Industry 5.0 SPC deployments, consistent with recent Quality 5.0 reviews that report limited empirical validation and missing operational metrics as persistent gaps (Bucci et al. 2026), is itself a motivation for an artifact-first contribution and for the proposition-driven agenda through which field evidence can subsequently be accumulated. Figure 1 situates SPC 5.0 within the broader landscape: it occupies the upper-right region, combining the highest digital/analytical maturity with the broadest sustainability scope, as the synthesis of the Industry 4.0/Quality 4.0 trajectory with Industry 5.0 priorities. Here, the vertical axis encodes digital and analytical maturity and the horizontal axis sustainability scope, so the placement expresses an inheritance relationship rather than a ranking: SPC 5.0 stems from the analytical maturity of the SPC 4.0/Quality 4.0 trajectory while extending scope along the sustainability dimension.

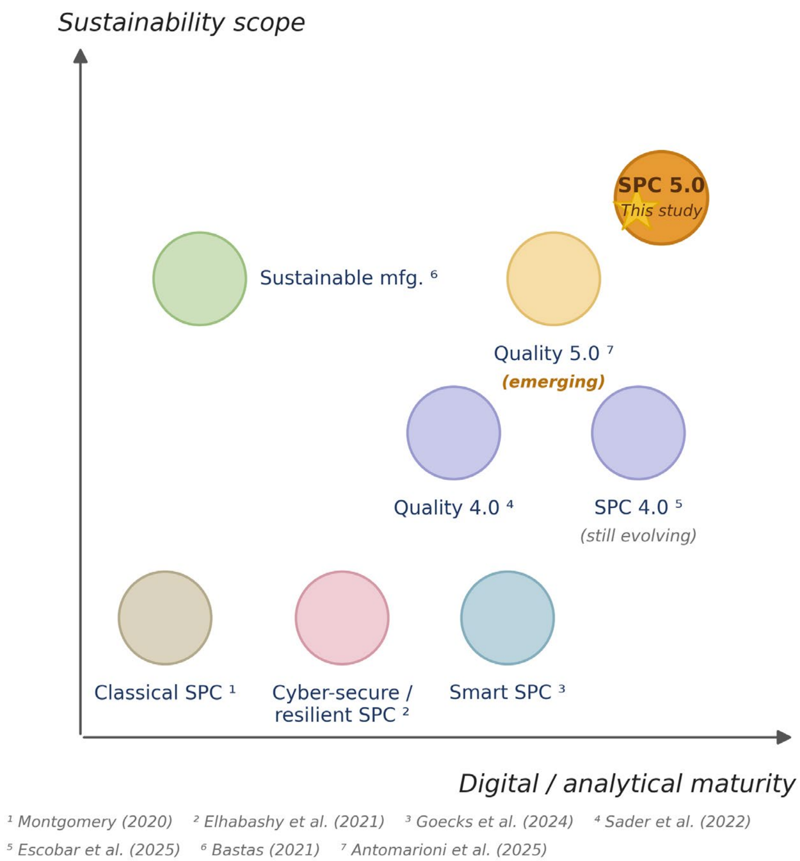

Figure 1. Conceptual positioning of SPC 5.0 relative to adjacent SPC and quality paradigms. Placements are qualitative and relative, synthesized from the cited literature.

Within this landscape, a substantial body of work has examined how AI and machine learning can extend statistical process monitoring. Reviews of statistical-learning and kernel-based methods document the use of classifiers, support vector and neural network models, and dimension reduction techniques to build data-driven control charts for high-dimensional and non-normal processes (Apsemidis et al. 2020; Tran et al. 2022). These methods complement the predictive, learning-based direction noted earlier, in which learning quality control (LQC) extends statistical quality control and SPC through machine learning classifiers (Escobar et al. 2025) and smart SPC architectures embed analytics within IIoT pipelines (Goecks et al. 2024). A recurring theme across this literature is that learning-based monitoring is most defensible when it augments, rather than replaces, the explicit limits and disciplined reaction logic of classical control charts, and when its outputs remain interpretable and validated. The present study adopts this position as a premise: it does not propose a new machine learning algorithm but specifies the design requirements under which intelligent monitoring can be incorporated into SPC without sacrificing statistical validity, human accountability, or resilience.

The key pillars of Industry 5.0 are presented in Table 1, along with their intent and implications for SPC design (Breque et al. 2021; van Erp et al. 2024).

Table 1. Industry 5.0 pillars and implications for SPC design (Breque et al. 2021; van Erp et al. 2024)

Industry 5.0 pillar	**Intent in production systems**	**Implications for SPC design and deployment**
Human-centricity	Operators as decision-makers; reduce cognitive load; skills development; accountability and trust in AI support.	Chart selection and rules must remain interpretable; escalation logic must specify roles; alerts must be explainable; training and visualization as part of design.

Sustainability	Monitor environmental and social impacts alongside conformance; reduce waste and energy per good unit; transparency across lifecycle.	Extend CTQCs to include energy/material intensity; link out-of-control actions to waste reduction; integrate quality costs and sustainability metrics in response.
Resilience	Maintain stable operations under disruptions (supply, demand, cyber, equipment); rapid recovery and learning.	Design for robust data pipelines, cyber protection, and fallback modes; validate models under drift; use randomization/robust rules where required; institutionalize learning loops.

To clarify the boundaries of the SPC 5.0 contribution, Table 2 contrasts SPC 5.0 with the Quality 4.0, smart SPC and SPC 4.0 frameworks from which it ascends, rendering explicit the design requirements that were omitted including human accountability, sustainability-augmented monitoring, and engineered resilience, while retaining classical statistical discipline.

Table 2. Positioning of SPC 5.0 relative to Quality 4.0, smart SPC and SPC 4.0

Dimension	Quality 4.0 / smart SPC / SPC 4.0	SPC 5.0 (this study)
Driving paradigm	Industry 4.0: digitalization, connectivity, big data, and AI/ML as quality enablers.	Industry 5.0: human-centricity, sustainability, and resilience as explicit design imperatives.
Primary objective	Faster, data-rich detection and predictive quality through digital enablement.	Statistically valid detection embedded in a socio-technical, multi-objective capability.
Role of the human	Often implicit; operator as a data source or recipient of alerts.	Explicit and accountable; operator/engineer as decision maker with explainable, role-aware support (DP3).
Role of AI / ML	Augments or, increasingly, automates detection and prediction.	Governed augmentation only; final disposition stays with qualified roles under change control (DP3, DP6).
Monitored variables	Conformance-centric CTQCs, expanded by available sensor data.	Conformance plus sustainability-augmented CTQCs (energy, material, safety) monitored jointly (DP4).
Resilience and security	Treated mainly as a data and IT-infrastructure concern.	Designed-in: pipeline validation, drift/anomaly detection, fallback sampling, cyber-awareness (DP5).
Improvement loop	Workflow closure and CAPA emphasized within smart SPC.	Workflow-closed with verified learning and recurrence prevention as a first-class requirement (DP2, DP6).

3. Methods

This study adopts a design science research logic, which is appropriate when knowledge is generated through the purposeful design and justification of an artifact (Hevner et al. 2004; Peffers et al. 2007). In this paper, the artifact comprises the SPC 5.0 design principles and the integrated framework that connect Industry 5.0 priorities to SPC design, escalation, and learning. To ground artifact construction in prior knowledge, the study uses a synthesizing review as opposed to a full systematic review, consistent with review approaches used to consolidate fragmented emerging domains and to generate integrative conceptual output (Tranfield et al. 2003; Snyder 2019).

The review and synthesis were conducted in the following steps. Literature relevant to conventional SPC design and deployment, Quality 4.0 and smart SPC, and Industry 5.0 was iteratively identified and screened for conceptual relevance. The retained sources were coded against recurring design themes: statistical validity, human interpretability and accountability, sustainability-related measurement, and resilience of digital monitoring infrastructures. These themes were subsequently translated into the implications summarized in Table 1 and then consolidated into the six SPC 5.0 design principles presented in Table 3 and into the integrated framework shown in Figure 2.

The artifact was developed following the six-activity design science research methodology of Peffers et al. (2007). Problem identification and motivation were established from the Quality 4.0 and SPC literature (Section 1); the objectives of a solution were set as the four research objectives; design and development produced the two artifacts (the design principles and the four-layer framework) through the coding-to-themes-to-principles procedure described above; demonstration was performed through the illustrative worked example (Section 4.2); evaluation is addressed analytically through the logical coherence and signal-detection behavior demonstrated for that example; and communication is served by the present paper, with confirmatory empirical evaluation framed as the testable propositions of Section 4.3. Two analytical procedures underpin the artifact. First, the design themes were mapped to design principles such that each principle is traceable to at least one source and to one or more framework layers, ensuring internal consistency. Second, the demonstration applies standard, fully specified Xbar-R and one-sided tabular CUSUM formulations (Montgomery 2020; Mitra 2021), so that every reported limit and decision parameter is reproducible from the Phase I estimates. Consistent with the literature reviewed in Section 2, the role of AI in the framework is deliberately scoped as governed decision support: learning-based models may rank candidate causes or surface context, but the study does not develop or train a new machine-learning algorithm, and any such model is required to operate under validation, versioning, and human authorization (DP3, DP6). Accordingly, validation is treated as two-staged: feasibility and logical coherence are demonstrated analytically in this paper, while predictive performance and field effects are deferred to the proposition-driven empirical agenda, which specifies the key constructs, comparisons, and metrics required for confirmatory evaluation.

To demonstrate how the artifact can be instantiated, an illustrative discrete machining scenario was developed. The purpose of this scenario was to provide a feasibility-level demonstration rather than empirical generalization, showing how the introduced SPC 5.0 design can be implemented through chart selection, multi-signal monitoring, escalation, and workflow closure. The monitored process was hypothesized to produce a critical diameter CTQC, measured in rational subgroups of n = 5 at regular intervals. In parallel, an energy-per-part indicator was considered to be captured from the machine controller as a sustainability-relevant CTQC (Bastas 2021). The worked example used a stable Phase I baseline (subgroups 1–15) followed by a tool-wear disturbance in Phase II. Simulated subgroup observations were generated to reflect plausible machining behavior: baseline diameter variation centered near target with within-subgroup standard deviation of approximately 0.020 mm, followed by a mean shift of about 0.050 mm and a realistic increase in dispersion after disturbance onset. Energy-per-part observations were generated with a corresponding upward drift under tool wear so that conformance deterioration and resource-use deterioration could be monitored jointly. No additional autocorrelation or adaptive model behavior was imposed, keeping the illustrative example focused on monitoring logic. Standard Xbar-R and one-sided CUSUM SPC chart formulations and decision logic were applied following Montgomery (2020) and Mitra (2021).

4. Results and Discussion

4.1 Design Principles and Conceptual Synthesis

Table 3 presents the SPC 5.0 design principles (DP1–DP6) derived from the synthesis. Collectively, these principles reposition SPC from a standalone charting technique to a governed monitoring capability in which statistical validity, human accountability, sustainability performance, and digital robustness are designed jointly. They do not replace classical SPC doctrine; they extend it so that Industry 5.0 priorities become explicit design requirements rather than afterthoughts (Montgomery 2020; Mitra 2021; Breque et al. 2021; van Erp et al. 2024).

Table 3. Proposed SPC 5.0 design principles and operationalization

Design principle	**Operationalization in SPC 5.0**
DP1. Statistical rigor first	Use Phase I/II separation; rational subgrouping; validated assumptions; avoid tampering; documented run rules (Montgomery 2020; Mitra 2021).
DP2. Workflow-closed SPC	Every signal triggers containment, diagnosis, corrective action, and verified closure in quality management system (QMS) / corrective and preventive action (CAPA); record decisions and outcomes for learning (Goecks et al. 2024).
DP3. Human-in-the-loop decision support	AI provides ranked hypotheses and context, but final disposition remains accountable to qualified roles; design for explainability and ergonomics (Breque et al. 2021).
DP4. Sustainability-augmented	Monitor environmental and social indicators such as energy, material

CTQCs	waste, and safety CTQCs in parallel with conformance metrics (Sader et al. 2022).
DP5. Resilience and cyber-aware monitoring	Protect integrity of measurement and features; include anomaly detection for sensor drift and cyber-physical attacks; implement fallback sampling (Elhabashy et al. 2021).
DP6. Continual learning with change control	When models or limits are updated, perform controlled validation; maintain versioning, traceability, and performance monitoring to avoid silent degradation (Escobar et al. 2021; Escobar et al. 2025).

As a result, SPC 5.0 is formulated as an end-to-end capability rather than a standalone statistical tool as conceptually demonstrated in Figure 2. The framework is lifecycle-oriented, commencing with what is measured and how trustworthy the data are, proceeding to how signals are generated and interpreted, and ending with how action, learning, and prevention are closed out. Industry 5.0 pillars are not confined to analytics alone; they also affect CTQC selection, alarm usability, accountability, and the persistence of learning across repeated events (Breque et al. 2021; van Erp et al. 2024).

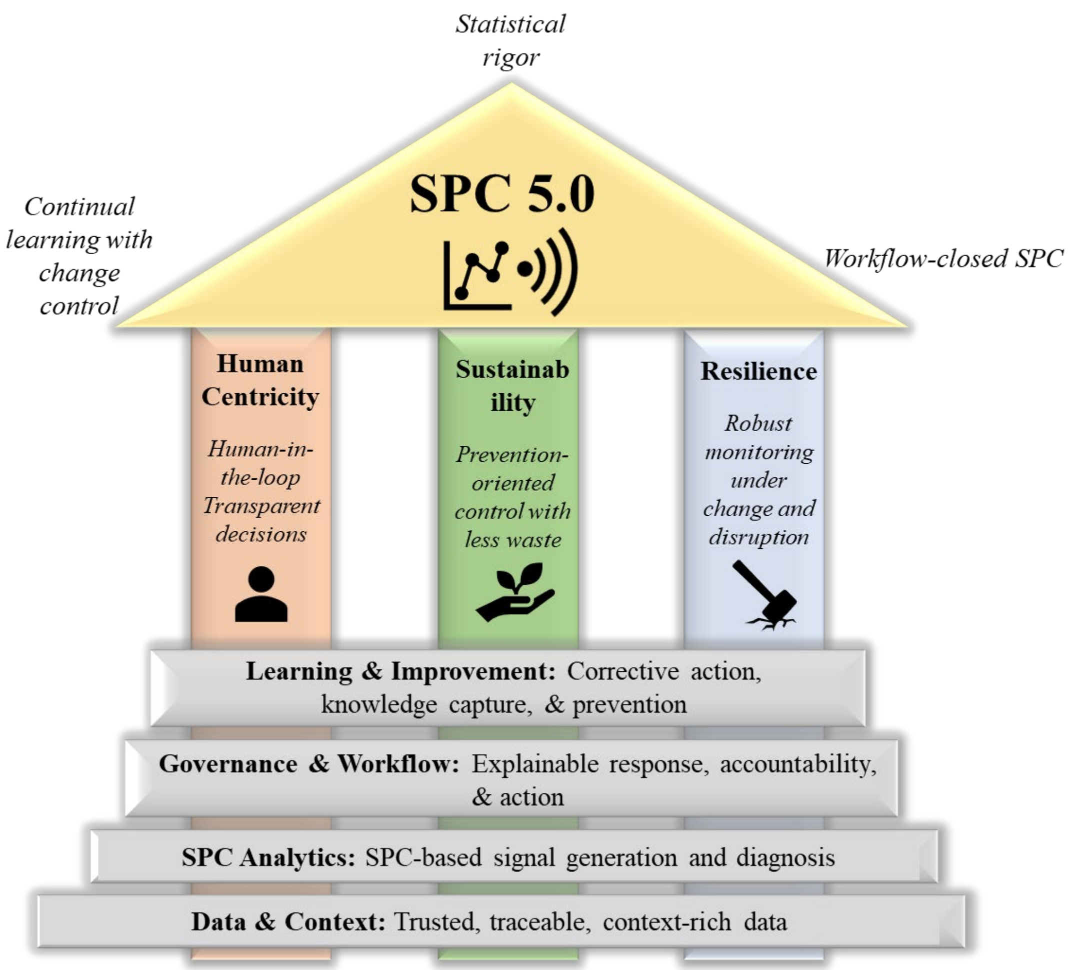

Figure 2. SPC 5.0 integrated framework connecting Industry 5.0 pillars to system layers

The *Data and Context* layer assumes high-frequency, connected environments without relaxing classical SPC prerequisites. Rational subgrouping, stable measurement systems, clear data definitions, and traceable data handling remain necessary if control limits and alarms are to be trusted (Montgomery 2020; Mitra 2021). Resilience enters at this layer through validation checks, traceability, fallback sampling or data-capture modes, and protections against sensor drift or cyber-physical disruption, all of which preserve monitoring continuity when digital infrastructure becomes unreliable (Dutta et al. 2021; Elhabashy et al. 2021).

The *Analytics* layer retains control charts as the primary decision discipline because they provide explicit limits and compatibility with disciplined reaction plans. Learning-based models may augment pattern recognition or diagnosis, but only under validation, governance, and change control. This layer also expands the monitored variable set beyond conformance-only CTQCs to include sustainability-relevant indicators such as energy or material intensity, provided these measures are operationally meaningful and interpreted with the same care as traditional quality characteristics (Bastas 2021; Escobar et al. 2021; Escobar et al. 2025; Sader et al. 2022).

The *Governance and Workflow* layer makes human-centricity operational. Signals should be explainable, role-aware, and accompanied by the context needed for disciplined response, so that operators and engineers can act with confidence rather than merely receiving opaque alerts (Breque et al. 2021; Antony et al. 2023). Within this bounded human–AI arrangement, digital tools can support triage by ranking plausible causes or surfacing contextual data, but authorization, disposition, and process change remain clearly assigned to accountable human roles. The *Learning and Improvement* layer closes the loop by converting each event into verified corrective action, captured knowledge, and recurrence prevention, which is essential if SPC 5.0 is to improve system performance rather than simply produce faster alarms.

4.2 Illustrative Worked Example

4.2.1 Monitoring Setup and Chart Design

The hypothesized context of the worked example was set as finish turning operation of a multi diameter, transmission shaft as illustrated in Figure 3. Phase I estimates were computed from subgroups 1–15 to establish the in-control baseline for the dimensional CTQC. The dimensional CTQC was hypothesized as the critical diameter of the transmission shaft, with a nominal target value of 50.000 mm. Phase I observations were simulated to remain close to this target, yielding an estimated in-control mean of 49.998 mm. An Xbar-R chart was selected, assuming rational subgroups of size n = 5 and the critical diameter continuously measured as a CTQC. The design assumes independence of observations within and between subgroups and approximate normality of subgroup means, consistent with classical SPC requirements (Montgomery 2020; Mitra 2021). The constants A2 = 0.577, D3 = 0, and D4 = 2.114 were used to obtain the limits shown in Table 4 (Montgomery 2020). For readability, reported chart parameters are displayed to three decimals, while the underlying limits and decision settings were computed from unrounded Phase I estimates. This choice deliberately remained in line with conventional SPC logic so that the added SPC 5.0 features can be examined without changing the underlying Shewhart discipline. Rational subgrouping was applied such that each subgroup captures short-term process variation under stable conditions, enabling separation of within-subgroup and between-subgroup variation for effective shift detection.

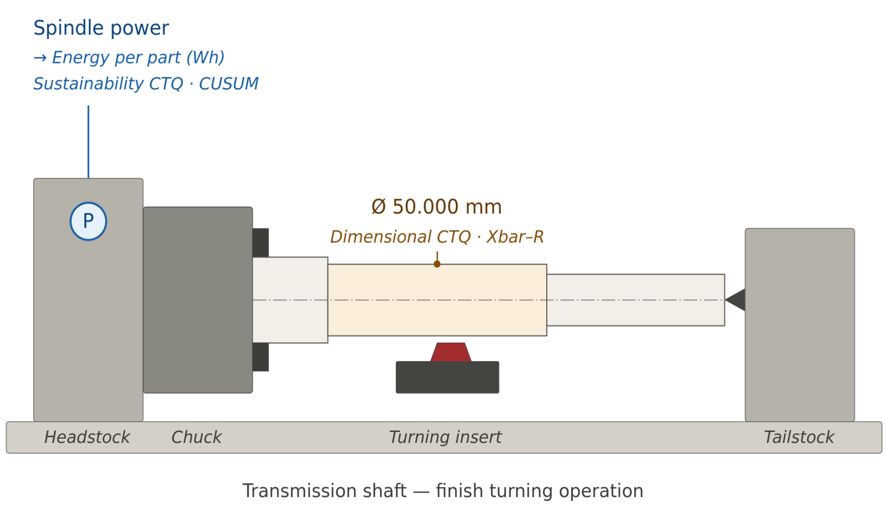

Figure 3. The hypothesized context of the worked example: finish turning operation of a transmission shaft

In parallel, the subgroup mean of energy consumption per part was assumed to be monitored as a sustainability CTQC using a one-sided (upper) tabular cumulative sum (CUSUM) chart. Phase I subgroups 1–15 were used to estimate the in-control target μ_0 and the standard deviation of the subgroup mean. In this study, the reported Energy SD (Phase I) corresponds to the standard deviation at the individual observation level, while the standard deviation of the subgroup mean is computed as $\sigma_{\bar{x}} = \sigma/\sqrt{n}$, where n = 5. Accordingly, the estimated value $\sigma_{\bar{x}} = 0.535$ is used for CUSUM design. Following standard design guidance, the reference value was set to $K = 0.5\sigma_{\bar{x}}$, corresponding to sensitivity to a mean shift of approximately one standard error of the subgroup mean, and the decision interval was set to $H = 5\sigma_{\bar{x}}$ (Montgomery 2020; Mitra 2021). These parameters are therefore expressed in units of the subgroup mean standard deviation $\sigma_{\bar{x}}$, ensuring consistency between the monitored statistic and the CUSUM accumulation scale. The Phase I baseline is assumed to represent stable process behavior; control limits and CUSUM parameters are therefore estimated from these subgroups and subsequently applied in Phase II for monitoring purposes. The intention is not to claim that these are universally optimal settings, but to show how a conventional sequential detection method can be repurposed to monitor resource-use deterioration within the same governance logic.

The one-sided CUSUM formulation adopted in the example is:
$C^+_t = \max\{0, C^+_{t-1} + [\bar{x}_{E,t} - (\mu_0 + K)]\}$; Signal an out-of-control condition if $C^+_t > H$;
where $\bar{x}_{E,t}$ denotes the subgroup mean of energy consumption at subgroup t.

Table 4. Control chart parameters and limits for the worked example

Parameter	**Value**
$\bar{\bar{x}}$ (Phase I, mm)	49.998
$\bar{R}$ (Phase I, mm)	0.050
$UCL_{\bar{x}}$ (mm)	50.026
$CL_{\bar{x}}$ (mm)	49.998
$LCL_{\bar{x}}$ (mm)	49.969
UCL_r (mm)	0.105
CL_r (mm)	0.050
LCL_r (mm)	0.000
Energy mean (Phase I, Wh)	119.830
Energy SD (individual, Phase I, Wh)	1.196
Energy SD of subgroup mean, $\sigma_{\bar{x}}$ (Wh)	0.535
CUSUM reference value, K (Wh)	0.268
CUSUM decision interval, H (Wh)	2.675

Table 5 reports the snapshot around the disturbance onset. From subgroup 16 onward, the simulated tool-wear condition raises both the dimensional mean and the energy mean, while subgroup 23 also produces a variability excursion. The example is therefore designed to illustrate three related monitoring logics within one scenario: Shewhart mean-shift detection, variability monitoring, and sustainability-oriented monitoring through cumulative evidence. While the introduced disturbance produces a relatively pronounced shift that is detectable by both Xbar and CUSUM charts at subgroup 16, the inclusion of the CUSUM chart demonstrates how sustained deviations in resource-use performance can be tracked and accumulated over time. It is noted that classical CUSUM advantages are most relevant for small and persistent shifts; however, in this illustrative scenario, the emphasis is on demonstrating integration of sustainability-related CTQCs within the SPC 5.0 monitoring framework rather than optimizing detection performance for marginal shifts.

Table 5. Snapshot of monitoring results around the disturbance onset

Subgroup	**x̄ (mm)**	**R (mm)**	**Energy mean (Wh)**	**x̄ signal**	**CUSUM signal**
14	49.988	0.040	120.020	No	No
15	50.001	0.058	119.430	No	No
16	50.053	0.031	130.870	Yes	Yes
17	50.057	0.064	131.710	Yes	Yes
18	50.043	0.037	133.800	Yes	Yes
19	50.044	0.051	129.000	Yes	Yes
20	50.047	0.063	128.860	Yes	Yes
21	50.060	0.074	133.570	Yes	Yes

4.2.2 Monitoring Results and Human-centric Escalation

Once an abnormal signal appears, the system initiates triage, presents role-relevant context, and supports human judgment. In the illustrated logic, digital support may surface ranked hypotheses or maintenance/context data, yet containment authorization and process changes remain assigned to accountable human roles, consistent with the human-centric governance intent of the framework (Breque et al. 2021; Antony et al. 2023). Against this escalation logic, Figure 4 presents the classical dimensional signals. The first Xbar out-of-control point occurs at subgroup 16, consistent with the introduced tool-wear shift, while the R chart remains stable until subgroup 23, where a higher within-subgroup spread indicates a variability event. This pattern is consistent with traditional SPC interpretation: the assignable cause first manifests as a location shift and only later as a more pronounced dispersion problem (Montgomery 2020; Mitra 2021). Analytically, the separation between the location signal at subgroup 16 and the dispersion signal at subgroup 23 traces the temporal signature of progressive tool wear, in which the mean migrates before within-subgroup spread degrades, a sequence that the Xbar-R pair resolves but a single summary statistic would conflate.

Figure 5 complements the dimensional view by showing a steadily increasing energy CUSUM after the disturbance onset. In this illustrative case, the CUSUM also crosses its decision interval at subgroup 16 and then continues to accumulate evidence of deterioration. As an analytical observation, the cumulative statistic rises monotonically from onset at an approximately constant per-subgroup increment, so the slope of the CUSUM path, not merely the threshold crossing, indexes the rate of resource-use deterioration and distinguishes a sustained drift from a transient excursion. The important point is not that the sustainability CTQC necessarily signals earlier than the dimensional CTQC in all cases, but that it provides a complementary monitoring perspective focused on resource intensity. As suggested by Mitra (2021) and Montgomery (2020), cumulative monitoring methods such as CUSUM are expected to be particularly valuable when small but persistent increases are present. During implementation and operationalization of the proposed SPC 5.0 framework, such gradual increases in sustainability indicators such as resource consumption may occur without immediate dimensional nonconformance. In such cases, sustainability-oriented CTQCs offer the potential of providing early indications of inefficiency or degradation that may not be immediately visible through conventional conformance metrics alone, contributing to sustainable manufacturing (Sader et al. 2022).

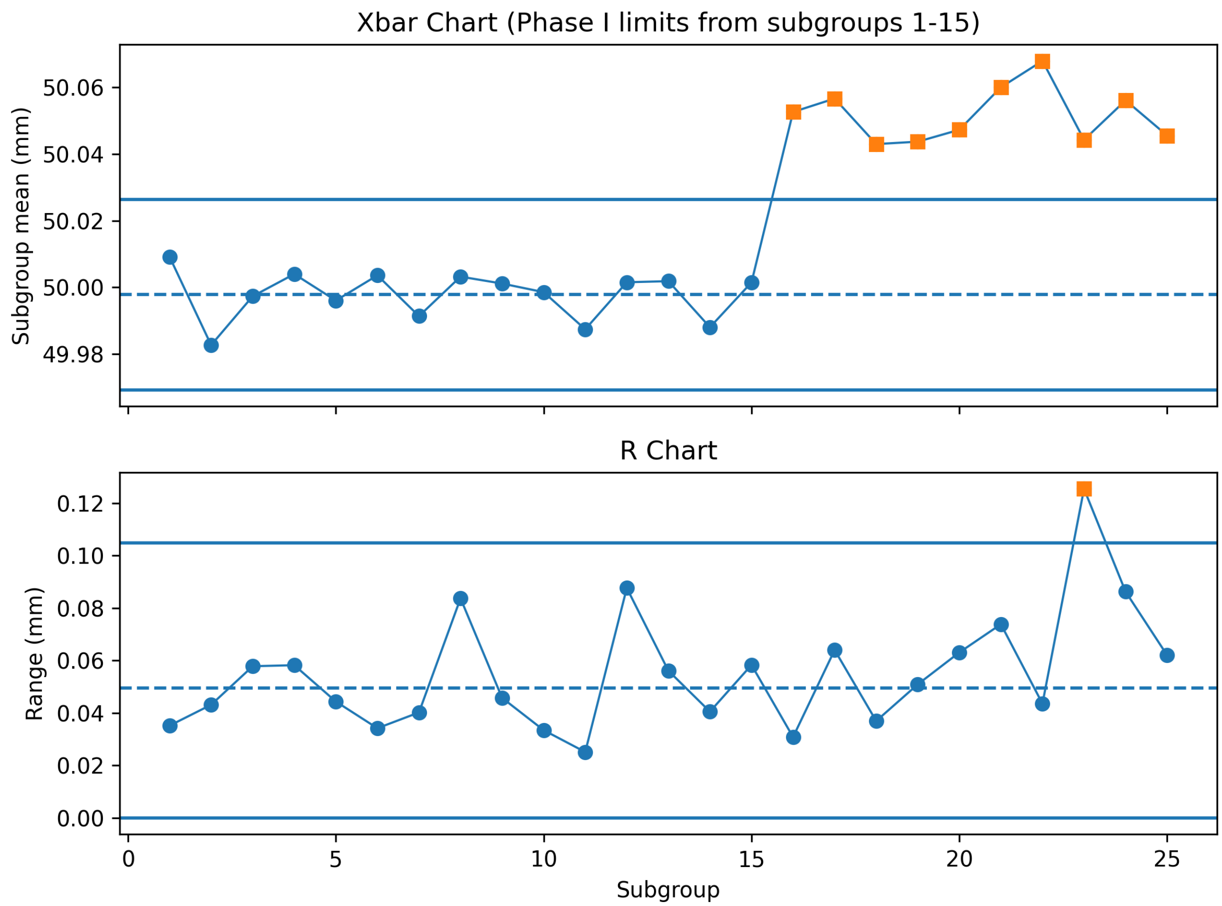

Figure 4. Xbar and R charts detecting a mean shift and a variability event

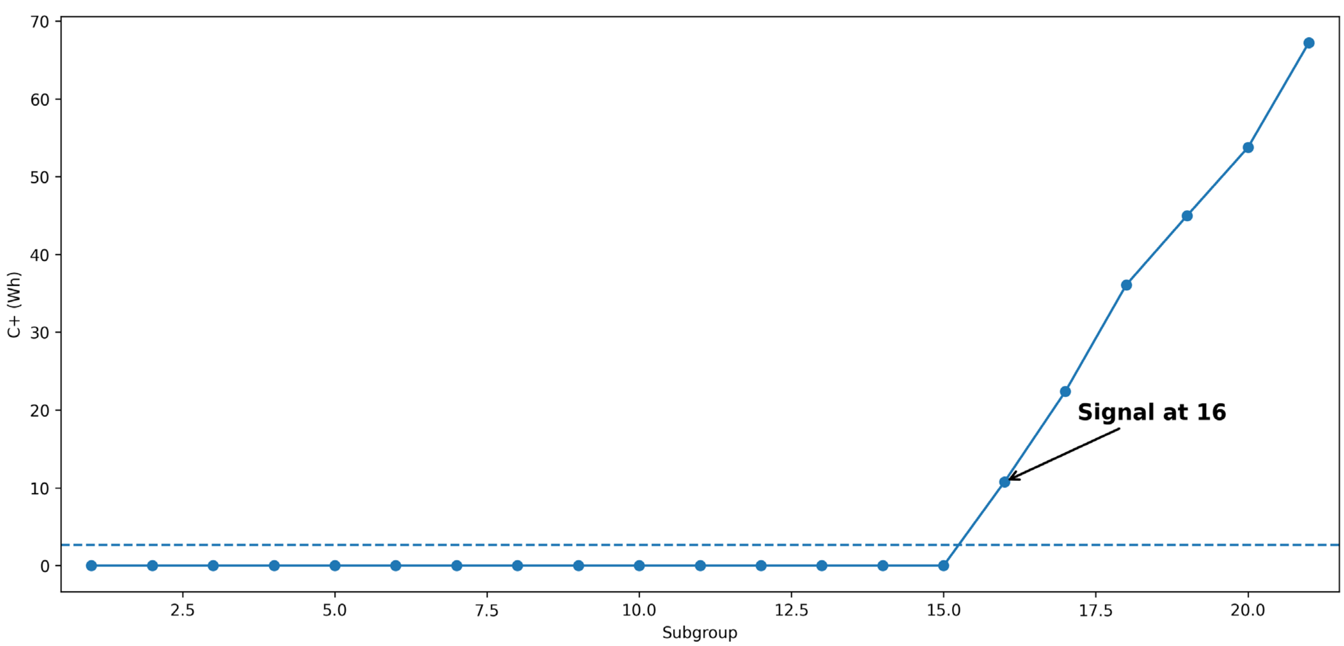

Figure 5. CUSUM chart indicating sustained energy increase under disturbance

A concise reaction plan that realizes the framework across design principles DP1–DP6 (DP5 and DP6 being only partially instantiated in this illustration) is:

- *Contain:* hold product produced since the last verified in-control subgroup; if the signal is confirmed, stop the operation or switch to a defined safe mode. (DP2, DP3)
- *Verify:* exclude measurement system or data-pipeline error through gage checks, timestamp or data-integrity checks, and basic sensor sanity checks before process adjustment. (DP1, DP5)
- *Diagnose:* review tool life, parameter changes, maintenance history, and other contextual data; where available, use AI-ranked hypotheses only as decision support rather than autonomous diagnosis. (DP3)
- *Correct and close:* implement the selected corrective action, confirm return-to-control with follow-up subgroups, document the event through CAPA or QMS, and record preventive learning to reduce recurrence. (DP2, DP4, DP6)

To make the added value explicit, the same scenario can be considered under a conventional, conformance-only SPC baseline. Traditional Xbar-R monitoring would detect the dimensional special cause, but the sustainability deterioration (in this case studied as energy-per-part) lies outside its monitored set and would accumulate unobserved; escalation would terminate at an alarm rather than a role-aware, workflow-closed disposition, and no data-integrity verification would precede adjustment. SPC 5.0 has been conceptualized to preserve the traditional statistical detection logic while extending monitoring coverage to the sustainability CTQCs (DP4), governing the response through accountable human roles (DP3), and embedding resilience and verification safeguards (DP1, DP5).

4.3 Deployment Implications, Propositions and Research Agenda

The proposed framework and feasibility demonstration led to various deployment implications. First, human-centric SPC requires alerts that are explainable, role-aware, and embedded in a defined response workflow; raw statistical signals alone are insufficient when response quality depends on comprehension, workload, and accountability (Breque et al. 2021; Antony et al. 2023). Second, sustainability-augmented CTQCs broaden what counts as process deterioration by treating waste-related outcomes such as energy intensity as legitimate monitoring targets alongside conformance. Third, resilience depends not only on chart performance but also on data validation, fallback arrangements, and governance mechanisms that keep monitoring credible under digital disturbance (Dutta et al. 2021; Elhabashy et al. 2021).

Deploying SPC 5.0 in real industrial environments nonetheless raises practical challenges that temper these implications. Data readiness is foundational: high-frequency sensing does not guarantee trustworthy data, so measurement system analysis, calibration, and time-stamp integrity must be sustained at scale before added analytics can be relied upon. Integration with existing manufacturing execution and quality management systems, and the consequent governance overhead of versioning models and limits, can be substantial. Human factors are equally demanding: realizing explainable, role-aware escalation requires training, interface design that mitigates alarm fatigue, and a culture in which operators are trusted to act, echoing the organizational readiness barriers reported for Quality 4.0 (Sony et al. 2020; Antony et al. 2023; Dutta et al. 2021). Sustainability-augmented monitoring adds instrumentation and costing effort to capture sustainability metrics such as energy or material intensity per conforming unit and demands governance rules that prevent secondary CTQCs from generating excess false alarms. Finally, learning-based augmentation introduces validation and drift management implications, and the same connectivity that enables it widens the cyber-physical attack surface, so resilience and change control are operating requirements rather than optional features (Elhabashy et al. 2021; Escobar et al. 2021). These challenges do not undermine the framework; rather, they indicate where implementation effort and the empirical agenda below should concentrate.

Table 6 translates the framework into four focused and testable propositions spanning human-centricity, sustainability, and resilience. Rather than offering a broad list of generic future directions, the table prioritizes the most central empirical questions and links each proposition to a mechanism and an indicative operationalization so that subsequent work can evaluate SPC 5.0 through field studies, quasi-experiments, action research, or design science evaluation across manufacturing and service settings (Hevner et al. 2004; Tranfield et al. 2003).

Table 6. Testable propositions for SPC 5.0 and suggested operationalization

ID	**Proposition**	**Mechanism (why)**	**Exemplar Operationalization (how to test)**
P1	Explainable, role-aware SPC signals supported by contextual decision information reduce time-to-containment and increase adherence to reaction plans compared with opaque alerting.	Explainability and role relevance reduce ambiguity and cognitive burden, strengthen operator trust, and improve disciplined response.	Compare cells or sites using explainable dashboards versus basic threshold alerts; measure trust, reaction-plan adherence, and time-to-containment from event logs and surveys.
P2	Adding sustainability-augmented CTQCs (e.g., energy or material intensity per conforming unit) alongside conformance CTQCs improves detection of economically, environmentally, and socially harmful deterioration without materially increasing false alarms when governance rules are defined.	Sustainability-related signals can expose latent waste or degradation before large volumes of nonconforming output accumulate, while disciplined governance limits overreaction.	Track conformance and sustainability CTQCs before and after implementation; evaluate detection timing, scrap, energy/material intensity, and false-alarm behavior.
P3	Higher governance and resilience maturity in SPC data pipelines (traceability, validation, drift monitoring, and fallback procedures) reduces missed detections and recovery time under sensor, integration, or cyber-physical disturbance.	Robust governance preserves signal integrity and monitoring continuity when disruptions or data-quality failures occur.	Construct a governance-maturity index and examine its relationship with missed-signal rate, downtime, and recovery time in observed disturbances or controlled simulations.
P4	Workflow-closed SPC, where signals are linked to CAPA/QMS closure and verified learning, reduces recurrence of known failure modes more effectively than signal-only SPC implementations.	Institutionalized closure converts detection into prevention by embedding corrective and preventive learning into everyday operations.	Use longitudinal CAPA records and process histories to compare recurrence rate, repeat deviations, and closure effectiveness across sites with different levels of workflow closure.

5. Conclusion

This paper revisited SPC design through an Industry 5.0 lens and proposed SPC 5.0 as a workflow-closed socio-technical monitoring capability rather than a standalone charting tool. The proposed SPC 5.0 view should be interpreted as an extension of the digital, workflow-closed, and governance-oriented SPC 4.0 foundation. By synthesizing Industry 5.0 principles with established SPC and Quality 4.0 literature, the paper produced two connected artifacts: six design principles (Table 3) and an integrated four-layer framework (Figure 2). Together, these artifacts preserve statistical rigor while making human-centricity, sustainability, and resilience explicit design requirements in monitoring, escalation, and learning (Montgomery 2020; Sony et al. 2020; Breque et al. 2021).
The objectives of the paper were met as follows. The review consolidated the implications of Industry 5.0 for SPC design. These implications were synthesized into the proposed design principles and framework. The worked example showed how classical Xbar-R and CUSUM monitoring can be combined with sustainability-augmented CTQCs and human-centric escalation without abandoning the conventional SPC discipline and formulations. Finally, the conceptual contribution has been translated into four focused propositions for subsequent empirical work.

The contribution should therefore be interpreted as a conceptual and design-oriented foundation for SPC 5.0, supported by an illustrative scenario. The paper demonstrated feasibility and coherence of the proposed logic; however, generalizable performance improvements are not claimed. Several limitations follow specifically from the illustrative, simulation-based nature of the example and should temper its interpretation. The subgroup observations were generated from a single discrete-machining scenario with an imposed mean shift and dispersion change; no autocorrelation, measurement error model, or adaptive process behavior was represented. The introduced disturbance is large and clearly assignable, so the example demonstrates joint, multi-characteristic monitoring rather than the small-shift detection performance for which CUSUM is classically preferred, and it does not support claims about average run length or false-alarm behavior under realistic conditions. The human-in-the-loop escalation and AI-ranked diagnosis are depicted conceptually rather than implemented, the sustainability dimension is reduced to a single energy-per-part proxy, and consequently DP5 and DP6 are only partially instantiated. These constraints, together with the reliance on simulated data and the absence of real-world Industry 5.0 SPC deployment evidence, define the boundary of what the demonstration establishes and motivate the empirical agenda.

Future studies are recommended to test the four propositions across different process types and digital maturity levels, paying particular attention to trust and cognitive load, quality–sustainability trade-offs, and resilience under drift or cyber-physical disturbance (Elhabashy et al. 2021; Escobar et al. 2021; Antony et al. 2023). Further fruitful areas for research include examining effect sizes in practice, refining governance and escalation mechanisms, and identifying the boundary conditions under which sustainability CTQCs and augmented decision support materially improve SPC and system performance.

References

Antomarioni, S., Fani, V., Bandinelli, R., Ciarapica, F.E. and Bevilacqua, M., Toward Quality 5.0: Integrating Industry 4.0, Human-Centricity, and Quality Management, *IFAC-PapersOnLine*, vol. 59, no. 10, pp. 1414–1419, 2025. https://doi.org/10.1016/j.ifacol.2025.09.238.

Antony, J., Sony, M., McDermott, O., Jayaraman, R. and Flynn, D., An exploration of organizational readiness factors for Quality 4.0: an intercontinental study and future research directions, *International Journal of Quality & Reliability Management*, 2023. https://doi.org/10.1108/IJQRM-10-2021-0357.

Apsemidis, A., Psarakis, S. and Moguerza, J.M., A review of machine learning kernel methods in statistical process monitoring, *Computers & Industrial Engineering*, vol. 142, 106376, 2020. https://doi.org/10.1016/j.cie.2020.106376.

Bastas, A., Sustainable manufacturing technologies: A systematic review of latest trends and themes, *Sustainability*, vol. 13, no. 8, 4271, 2021. https://doi.org/10.3390/su13084271.

Breque, M., De Nul, L. and Petridis, A., *Industry 5.0: Towards a sustainable, human-centric and resilient European industry*, European Commission, Directorate-General for Research and Innovation, Publications Office of the European Union, 2021. https://doi.org/10.2777/308407.

Bucci, I., Fani, V., Rossi, M., Bandinelli, R. and Tucci, M., Quality 5.0: a systematic literature review and a gap-driven research agenda, *The TQM Journal*, vol. ahead-of-print, no. ahead-of-print, pp. 1–23, 2026. https://doi.org/10.1108/TQM-12-2025-0747.

Dutta, G., Kumar, R., Sindhwani, R. and Singh, R.K., Digitalization priorities of quality control processes for SMEs: a conceptual study in perspective of Industry 4.0 adoption, *Journal of Intelligent Manufacturing*, vol. 32, no. 6, pp. 1679–1698, 2021. https://doi.org/10.1007/s10845-021-01783-2.

Elhabashy, A.E., Dastoorian, R., Wells, L.J. and Camelio, J.A., Random sampling strategies for multivariate statistical process control to detect cyber-physical manufacturing attacks, *Quality Engineering*, vol. 33, no. 2, pp. 300–317, 2021. https://doi.org/10.1080/08982112.2020.1838541.

Escobar, C.A., McGovern, M.E. and Morales-Menendez, R., Quality 4.0: a review of big data challenges in manufacturing, *Journal of Intelligent Manufacturing*, vol. 32, no. 8, pp. 2319–2334, 2021. https://doi.org/10.1007/s10845-021-01765-4.

Escobar, C.A., Cantoral-Ceballos, J.A. and Morales-Menendez, R., Quality 4.0: Learning quality control, the evolution of SQC/SPC, *Quality Engineering*, vol. 37, no. 1, pp. 92–117, 2025. https://doi.org/10.1080/08982112.2024.2356519.

Goecks, L.S., Habekost, A.F., Coruzzolo, A.M. and Sellitto, M.A., Industry 4.0 and Smart Systems in Manufacturing: Guidelines for the Implementation of a Smart Statistical Process Control, *Applied System Innovation*, vol. 7, no. 2, 24, 2024. https://doi.org/10.3390/asi7020024.

Hevner, A.R., March, S.T., Park, J. and Ram, S., Design science in information systems research, *MIS Quarterly*, vol. 28, no. 1, pp. 75–105, 2004. https://doi.org/10.2307/25148625.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T. and Hoffmann, M., Industry 4.0, *Business & Information Systems Engineering*, vol. 6, no. 4, pp. 239–242, 2014. https://doi.org/10.1007/s12599-014-0334-4.

Mitra, A., *Fundamentals of Quality Control and Improvement*, 5th Edition, John Wiley & Sons, 2021. https://doi.org/10.1002/9781119692379.

Montgomery, D.C., *Introduction to Statistical Quality Control*, 8th Edition, John Wiley & Sons, 2020. ISBN: 9781119723097.

Nelson, L.S., The Shewhart control chart—tests for special causes, *Journal of Quality Technology*, vol. 16, no. 4, pp. 237–239, 1984. https://doi.org/10.1080/00224065.1984.11978921.

Peffers, K., Tuunanen, T., Rothenberger, M.A. and Chatterjee, S., A design science research methodology for information systems research, *Journal of Management Information Systems*, vol. 24, no. 3, pp. 45–77, 2007. https://doi.org/10.2753/MIS0742-1222240302.

Sader, S., Husti, I. and Daroczi, M., A review of Quality 4.0: definitions, features, technologies, applications, and challenges, *Total Quality Management & Business Excellence*, vol. 33, no. 9–10, pp. 1164–1182, 2022. https://doi.org/10.1080/14783363.2021.1944082.

Schoonhoven, M. and Does, R.J.M.M., The $\bar{X}$ control chart under non-normality, *Quality and Reliability Engineering International*, vol. 26, no. 2, pp. 167–176, 2010. https://doi.org/10.1002/qre.1029.

Snyder, H., Literature review as a research methodology: An overview and guidelines, *Journal of Business Research*, vol. 104, pp. 333–339, 2019. https://doi.org/10.1016/j.jbusres.2019.07.039.

Sony, M., Antony, J. and Douglas, J.A., Essential ingredients for the implementation of Quality 4.0: a narrative review of literature and future directions for research, *The TQM Journal*, vol. 32, no. 4, pp. 779–793, 2020. https://doi.org/10.1108/TQM-12-2019-0275.

Tran, P.H., Ahmadi Nadi, A., Nguyen, T.H., Tran, K.D. and Tran, K.P., Application of machine learning in statistical process control charts: a survey and perspective, in *Control Charts and Machine Learning for Anomaly Detection in Manufacturing*, K.P. Tran (ed.), Springer Series in Reliability Engineering, Springer, Cham, pp. 7–42, 2022. https://doi.org/10.1007/978-3-030-83819-5_2.

Tranfield, D., Denyer, D. and Smart, P., Towards a methodology for developing evidence-informed management knowledge by means of systematic review, *British Journal of Management*, vol. 14, no. 3, pp. 207–222, 2003. https://doi.org/10.1111/1467-8551.00375.

van Erp, T., Pereira Carvalho, N.G., Gerolamo, M.C., Gonçalves, R., Rytter, N.G.M. and Gladysz, B., Industry 5.0: A new strategy framework for sustainability management and beyond, *Journal of Cleaner Production*, vol. 461, 142271, 2024. https://doi.org/10.1016/j.jclepro.2024.142271.

Xu, L.D., Xu, E.L. and Li, L., Industry 4.0: state of the art and future trends, *International Journal of Production Research*, vol. 56, no. 8, pp. 2941–2962, 2018. https://doi.org/10.1080/00207543.2018.1444806.

Zhong, R.Y., Xu, X., Klotz, E. and Newman, S.T., Intelligent manufacturing in the context of Industry 4.0: a review, *Engineering*, vol. 3, no. 5, pp. 616–630, 2017. https://doi.org/10.1016/J.ENG.2017.05.015.

Zonnenshain, A. and Kenett, R.S., Quality 4.0 - the challenging future of quality engineering, *Quality Engineering*, vol. 32, no. 4, pp. 614–626, 2020. https://doi.org/10.1080/08982112.2019.1706744.

Biography

Asst. Prof. Dr. Ali Baştaş is an Assistant Professor in the Department of Industrial Engineering at Eastern Mediterranean University (Northern Cyprus). He earned B.Eng. and M.Eng. degrees in Mechanical Engineering (Manufacturing and Management) from the University of Bath (UK) and a Ph.D. in Engineering Management from the University of Derby (UK). Prior to academia, he held international roles in operational excellence, engineering leadership, and supplier development. He is a Chartered Quality Professional, a Lean Six Sigma Green Belt, and an ISO 9001 Lead Auditor. His research focuses on quality engineering and digital transformation of quality, sustainable operations and supply chains, and resilience-oriented manufacturing systems.