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Automation Efficiency in Cyber-Physical Systems: Interaction Between Technical Performance and Algorithmic Intelligence

Iliyan Vasilev Vasilev
University of Chemical Technology and Metallurgy, Sofia, Bulgaria

ABSTRACT: The performance of a cyber-physical system cannot be judged reliably from a single engineering variable. In the investigated micro-CPS, response time, communication latency and throughput describe the technical layer, whereas prediction accuracy captures the contribution of the learning component. The present paper examines how these two dimensions interact and how their combined effect is reflected in an overall efficiency index. A quasi-experimental comparison was carried out for a logistics and warehouse control configuration equipped with connected sensing, real-time data exchange and machine-learning support, and for a functionally similar conventional automated system. The empirical analysis was based on six variables, which were first standardized using z-scores and then assigned to four domains: technical efficiency, algorithmic intelligence, resource and energy efficiency, and economic efficiency. A clear difference emerged between the two system architectures. The CPS produced a mean composite index of 0.954, whereas the conventional automated system had a mean value of −0.954. The regression results further showed that technical efficiency and algorithmic intelligence contributed most strongly to the overall index. Of particular interest was their interaction. The interaction between technical efficiency and algorithmic intelligence was statistically significant ($B = 0.154$, $\beta = 0.267$, $p = 0.004$). This interaction included to the model increased R^2 from 0.93 to 0.95. The finding indicates that the contribution of algorithmic intelligence to overall system performance depends, at least partly, on the level of technical efficiency achieved by the system. Rather, their contribution becomes more pronounced when the control and communication infrastructure already performs reliably. The sensitivity analysis led to the same overall ordering of the two architectures under alternative weighting schemes. Within the scope of the available dataset, this provides additional evidence that the observed difference is not simply an artefact of the selected weights.

KEYWORDS: algorithmic intelligence, cyber-physical systems, composite index, interaction effect, industrial automation, technical efficiency.

INTRODUCTION

Cyber-physical systems are distinguished from conventional automation by the continuous exchange between physical processes and digital decision mechanisms. Sensors provide the state of the process, communication channels carry these measurements, computational units interpret them, and actuators close the loop. In practical engineering terms, the quality of this loop depends on timing, reliability, communication performance and the ability of the control logic to respond to changing conditions [1–3]. The increasing use of machine-learning modules adds another layer: the system is expected not only to execute control rules, but also to extract patterns from operational data and use them in subsequent decisions.

This creates a measurement problem. A low communication delay does not by itself demonstrate that a CPS is effective, just as a high prediction accuracy says little about the physical process if control actions are slow or unstable. Production indicators such as availability, throughput and cycle time remain useful, but they describe only part of the behaviour of an integrated cyber-physical architecture. The NIST framework similarly treats timing, interoperability, trustworthiness and system behaviour as related concerns [4]. Research on cyber-physical production systems therefore tends to move from isolated indicators toward system-level assessment [3,5].

The evaluation framework used here was developed around five conceptual domains: technical efficiency, algorithmic intelligence, cybersecurity, resource and energy efficiency, and economic efficiency. Only four of them are represented by quantitative indicators in the available empirical dataset; no primary cybersecurity variable was recorded for the calculation reported in this paper. The present analysis consequently concentrates on the four measured domains, with particular attention to the relation between technical efficiency and algorithmic intelligence.

The research question is narrower than a general assessment of CPS performance: does the algorithmic component contribute independently to system efficiency, or does its contribution depend on the quality of the technical layer? To answer this, the domain indices are first compared with the composite efficiency index and then entered into regression models, including an explicit ITE×IAI interaction term. Stability under alternative weighting schemes is examined as an additional check on the composite result.

MATERIALS AND METHODS

Study design and systems

The study compared the two systems over a period of sixteen weeks under normal operating conditions. A fully randomized experiment was not practical, since both systems were already embedded in ongoing logistics and warehouse activities. Thus quasiexperimental study was adopted. System A represented a small-scale cyber-physical configuration. Sensor data were collected continuously and exchanged through the communication infrastructure, while an analytical layer supported decisions concerning stock levels, movement of goods, and the processing of operational requests. Machine-learning functions were also available as part of this decision-support process. System B was selected at the conventional counterpart because it performed broadly similar tasks in the same type of operational setting. Its control logic respectively relied on predefined rules and standard automation procedures, without an adaptive or self-learning analytical component.

The empirical records were obtained from system logs, sensor measurements, system reports, simulation outputs and the experimental infrastructure. The dataset reported for the primary indicators contains 384 observations per system. This scale is adequate for the intended comparison, but the investigated configuration remains a micro-CPS; the findings should therefore be read as evidence from a bounded engineering case rather than as a general estimate for large industrial installations. The inferential tables in the underlying analysis were produced at an aggregated level, which is discussed later as a limitation when interpreting model statistics.

Indicators and domain indices

Six variables were included in the analysis, each representing a measurable aspect of system performance. Response time, communication latency, and energy consumption were interpreted as inverse indicators, due to the lower values known to correspond to more efficient operation. The amount of material, data, or items that a system processes, delivers, or handles within a specific period of time, prediction accuracy, and return on investment (ROI) were treated in the opposite way, with higher values indicating better performance. Energy consumption was again treated as a cost-type measure. The technical efficiency index (ITE) combines response time, latency and throughput. Prediction accuracy represents the algorithmic intelligence index (IAI), energy consumption represents the resource and energy efficiency index (IREE), and ROI represents the economic efficiency index (IECO). Cybersecurity belongs to the wider conceptual framework but is not included in the empirical composite index because the corresponding primary measurement was not available.

Table I (1). Empirical indicators and index domains

Domain index	Primary indicator	Direction	Unit
ITE	Response time	Lower is better	s
ITE	Latency	Lower is better	ms
ITE	Throughput	Higher is better	operations/s
IAI	Prediction accuracy	Higher is better	ratio / %
IREE	Energy consumption	Lower is better	kWh
IECO	Return on investment	Higher is better	ratio / %

Normalization and index construction

The variables are expressed in different units, so direct aggregation would give excessive influence to measurements with larger numerical ranges. Each indicator was therefore transformed to a z-score, $z=(x-\mu)/\sigma$. For response time, latency and energy

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use, the standardized sign was reversed so that a larger value always denoted a more favourable state. This common direction is necessary before combining the variables into domain scores [6].

Within each domain, standardized indicators were averaged. The composite efficiency index was calculated as $CI=\Sigma w_i I_i$. Equal weights (0.25 for each of the four measured domains) were used as the baseline because the empirical analysis did not assume that one domain should dominate the others in advance. Two alternative weight structures were used for sensitivity checking: a technically oriented scheme (ITE 0.35, IAI 0.30, IREE 0.20, IECO 0.15) and a resource-economic scheme (ITE 0.20, IAI 0.20, IREE 0.30, IECO 0.30).

Statistical analysis

Statistical processing was carried out in SPSS 21. Descriptive statistics were followed by a reliability check and exploratory factor analysis of the indicator structure. Pearson coefficients were used to inspect the association of each domain index with CI. A General Linear Model (GLM) tested the difference between system types, while binary logistic models examined how well the domain indices distinguished the CPS from the conventional architecture. A multiple linear regression estimated the contribution of ITE, IAI, IREE and IECO to CI. The main analysis then added the product term ITE×IAI to determine whether technical and algorithmic performance interacted. Alternative weights and a one-at-a-time ±20% sensitivity test was used to assess how dependent the final index was on the chosen weighting structure.

RESULTS

Descriptive characteristics and measurement structure

Descriptive characteristics and measurement structure

The six indicators showed enough variation to make a meaningful comparison between the systems. Response time ranged from 0.86 to 2.40 s, with a mean of 1.588 s (SD = 0.581), while communication latency varied between 6.3 and 21.0 ms, averaging 13.091 ms (SD = 5.498). Throughput values extended from 320 to 575 operations per second and had a mean of 446.25 (SD = 93.696). Prediction accuracy ranged from 0.72 to 0.99, with an average of 0.8516 (SD = 0.105). Energy use varied from 97 to 150 kWh, producing a mean of 122.84 kWh (SD = 22.78), whereas ROI ranged from 0.11 to 0.40 and averaged 0.233 (SD = 0.100). The tested subset also showed high internal consistency, with Cronbach's alpha equal to 0.90. In the exploratory factor analysis, the first component was clearly dominant, with an eigenvalue of 5.951 and accounting for 99.179% of the total variance.

Composite efficiency index

The composite score produced a clear separation between the two architectures. The conventional automated system had a mean CI of -0.954 (SD 0.190), whereas the micro-CPS reached 0.954 (SD 0.260). The difference between the group means was therefore 1.908 standardized index units. Both groups contained 384 descriptive observations. The sign of the scores is a consequence of the standardization procedure; it should be interpreted comparatively rather than as an absolute efficiency scale.

Table II (2). Composite efficiency index by system type

System	Mean CI	SD	N
Conventional automated system	-0.954	0.190	384
Cyber-physical system	0.954	0.260	384

Relationships among domain indices

The domain indices were associated with CI to different degrees. Technical efficiency had the strongest correlation (r=0.86), followed secondly by algorithmic intelligence (r=0.82), resource and energy efficiency (r=0.79), and economic efficiency (r=0.68). Correlations among the domain indices themselves were lower: ITE–IAI r=0.62, ITE–IREE r=0.71, ITE–IECO r=0.48, IAI–IREE r=0.65, IAI–IECO r=0.44, and IREE–IECO r=0.52. The pattern is useful because it shows that the four scores move together without being interchangeable. In particular, technical and algorithmic performance are related, but not so strongly that one can be treated as a substitute for the other.

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Between-system and predictive analyses

The GLM showed a clear difference between the two system types, with the composite index varying significantly by architecture ($F = 562.325$, $p < 0.001$). The model explained 94.9% of the observed variance, with an adjusted R^2 of 0.948. The logistic regression produced a similar picture. Taken together, the four domain indices significantly distinguished the CPS from the conventional system ($\chi^2 = 35.180$, df = 4, $p < 0.001$), and 90.6% of the observations were classified correctly. The corresponding Nagelkerke R^2 was 0.889, while the Hosmer–Lemeshow test was non-significant ($p = 1.000$). These results point to a strong separation between the two architectures in the present sample. At the same time, the unusually high effect sizes should be read cautiously, given the restricted case design and the way the observations were aggregated for the inferential analyses.

Table III (3). Univariate discrimination by domain index

Index	B	p	Exp(B)	Nagelkerke R^2	Correct classification
ITE	2.713	0.007	15.072	0.611	75.0%
IAI	2.401	0.004	11.032	0.586	78.1%
IREE	2.529	0.004	12.541	0.612	75.0%
IECO	1.481	0.009	4.399	0.379	68.8%

When the domains were examined separately, ITE, IAI and IREE showed the greatest discriminatory value, while IECO remained significant but weaker. The same ordering appeared in the linear regression for CI. That model explained 93% of the variance (adjusted R^2=0.92; F=87.4, p<0.001). The largest standardized coefficient belonged to technical efficiency (β=0.412, p<0.001), followed by algorithmic intelligence (β=0.351, p<0.001), resource and energy efficiency (β=0.296, p=0.001), and economic efficiency (β=0.188, p=0.012). Thus, the two domains highlighted in the title were already the leading individual contributors before their interaction was introduced.

Interaction and sensitivity analysis

The interaction analysis performs a further layer to the comparison. If added the ITE × IAI term into the regression, the proportion of explained variance rose from 0.93 to 0.95 (adjusted $R^2 = 0.94$; $F = 92.7$, $p < 0.001$). The interaction itself was positive and statistically significant ($B = 0.154$, $\beta = 0.267$, $p = 0.004$). This pattern suggests that gains in technical efficiency were associated with a larger improvement in the composite index when algorithmic intelligence was also high. The contribution of the learning component appeared to depend partly on the quality of the underlying control and communication environment: stronger technical performance provided better conditions for the algorithmic layer to translate its predictive capability into overall system performance.

Changing the domain weights did not alter the ordering of the systems. With equal weights, the conventional system and CPS scored -0.954 and 0.954, respectively. The technically oriented scheme produced -0.967 and 0.981, while the resource-economic scheme produced -0.931 and 0.927. In the ±20% tornado analysis, CI was most sensitive to ITE (range 0.14), then IAI (0.12), IREE (0.09) and IECO (0.07). The source sensitivity scenario also lists a smaller value for the conceptual cybersecurity term (0.04), although cybersecurity was not part of the four-domain empirical CI. The modest score changes under the tested scenarios indicate that the observed ranking is not an artefact of one particular set of weights.

Table IV (4). Sensitivity of system ranking to alternative domain weights

Weighting scheme	Conventional CI	CPS CI
Equal: 0.25/0.25/0.25/0.25	-0.954	0.954
Technical-oriented: 0.35/0.30/0.20/0.15	-0.967	0.981
Resource-economic: 0.20/0.20/0.30/0.30	-0.931	0.927

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DISCUSSION

The more important finding is not merely that the CPS achieved a higher composite score. The regression results show more precisely where that advantage comes from. Technical efficiency and algorithmic intelligence made the strongest individual contributions to CI, while their interaction explained additional variation beyond the additive model. This suggests that the two domains should not be viewed as separate sources of improvement. Instead, their effects appear to reinforce one another: the value of stronger algorithmic capability depends partly on the technical conditions in which it operates, just as improvements in the technical layer become more consequential when supported by a capable analytical component.

Such a result is consistent with the engineering logic of CPS. Computation and physical dynamics are coupled through sensing, communication and actuation [1,2]. The 5C architecture expresses a similar progression from connection and data conversion toward cognition and configuration [5]. In that sequence, an intelligent decision layer cannot compensate indefinitely for poor timing, unstable communication or weak throughput. Conversely, a technically fast system gains limited adaptive value if its analytical component does not interpret the incoming data with sufficient accuracy. The significant ITE×IAI term gives a quantitative expression to this interdependence within the present dataset. Related manufacturing studies likewise associate CPS-based automation with improved coordination, prediction and operational control [3,7].

The very high explanatory power of the GLM ($R^2 = 0.949$), together with the 90.6% classification accuracy, should be interpreted within the limits of this particular case rather than as evidence of general performance across CPS applications. The comparison was based on a single micro-CPS and one conventional system selected because the two performed broadly similar functions. There is also a difference in the level at which the data appear to have been analysed. The descriptive results include 384 observations for each system, whereas the GLM reports 30 error degrees of freedom, indicating that at least part of the inferential analysis was carried out on aggregated data. The weighting experiment addresses a different methodological concern. Composite indices are often sensitive to the analyst's choice of weights, especially when one domain has much stronger numerical variation than another. Here, moving from equal weights to either a technical emphasis or a resource-economic emphasis changed the numerical CI values only modestly and did not reverse the comparison. This is encouraging for engineering use because priorities will differ between applications: a motion-control system may place more weight on latency, while an energy-management application may place more weight on consumption and resource use. The present result suggests that such moderate shifts in emphasis would not change the central conclusion for the two systems examined.

Cybersecurity remains the clearest gap in the empirical implementation. It is part of the five-domain conceptual model because a compromised communication or control function can propagate directly to the physical process [4]. Nevertheless, no primary cybersecurity variable appears in the empirical indicator table used to construct CI. For that reason, the numerical index analysed here is explicitly a four-domain index. A subsequent validation should include measured security variables—such as detection time, recovery time, incident frequency or a standardized vulnerability measure—and then repeat the factor, regression and sensitivity analyses. Until that is done, cybersecurity should be discussed as a conceptual extension rather than as an empirically validated component of the present score.

From an automation-engineering perspective, the value of the method lies in keeping the domain scores visible. A single CI can be useful for comparing architectures, but the diagnostic information is carried by ITE, IAI, IREE and IECO. For commissioning, modernization or digital-twin studies, this makes it possible to distinguish a communication or control bottleneck from a problem of prediction quality, energy demand or economic return. The composite value is therefore best used as a summary of the engineering evidence, not as a replacement for the underlying measurements.

CONCLUSION

The findings suggest that technical efficiency and algorithmic intelligence should not be treated as entirely separate influences on CPS performance. In the micro-CPS examined here, their interaction was positive and statistically significant, and adding the ITE × IAI term increased the proportion of explained variance in the composite index from 0.93 to 0.95. The CPS also remained ahead of the conventional automated system when alternative weighting schemes were applied. Taken together, these results suggest that, in this case, system efficiency depended on how effectively the technical infrastructure and the intelligent decision layer worked together. Further testing is needed before this relationship can be generalized. A useful next step would be to examine the same interaction across larger and more varied automated systems, state the level of data aggregation clearly, and incorporate cybersecurity as an empirically measured fifth domain rather than leaving it only within the conceptual framework.

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