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Prioritizing Human-Centric and Social Life Cycle Assessment (S-LCA) Criteria in Industry 4.0 and 5.0 Technologies Using an Integrated AHP-TOPSIS-VIKOR Framework

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Abstract

The fast growth of digital technologies in Industry 4.0 brought monumental developments in automation systems and efficiency rates. However, the recent shift to Industry 5.0 has brough its own demands, this time the integration of human-centered, sustainable, and resilient approach into the manufacturing environment. This research establishes a strong Multi-Criteria Decision-Making (MCDM) framework to meet this imperative knowledge gap in sustainable evaluation of innovative manufacturing and digital technologies. A thorough comparison of ten criteria of sustainability to environmental, economic as well as social indicators was conducted via Analytic Hierarchy Process (AHP) in order to determine their weighted importance. The process of evaluation included the application of Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and VIKOR method to a seven-emerging technology decision-making matrix. Tech C maintained the highest degree of sustainability among any of the alternatives with the TOPSIS value of 0.8106 and recorded a zero VIKOR value. The identical rankings being reached by both TOPSIS and VIKOR methods confirm the credibility of the model. The research provides a technical assessment method which allows stakeholders to select technologies based on Industry 5.0 philosophies through a framework that can be used for pragmatic and repetitive application.

Keywords: Human-Centric, Social life cycle assessment, Industry 4.0 and 5.0 technologies, AHP-TOPSIS-VIKOR framework.

1 | Introduction

In the past decade we have seen a transformation in the manufacturing environment which is as a result of the introduction of Industry 4.0 (IR4.0), that has brought along digital technologies like Internet of Things

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(IoT), Artificial Intelligence (AI), big data analytics, Cyber-Physical Systems (CPS) and smart robots to what used to be very much traditional manufacturing [1], These technologies which provides real-time data collection capabilities, alongside automated processes and intelligent decision capabilities, together provide and produce increased productivity together with operation efficiency and flexible outcomes for manufacturing industries. Recently, Industry 5.0 (IR5.0) has emerged to complement the many progresses that has been made in the manufacturing environment. The IR5.0 which seeks to revitalize industry through human-focused technology innovation is aim to promotes durability together with environmental sustainability [2].

While theoretical possibilities of IR4.0 and IR5.0 to bring about sustainability are extremely well recognized internationally, empirical research evaluating actual deployments indicate a crucial lack in regards to the application of quantitative and qualitative performance measures. Most sustainable digital change research is predominantly biased toward quantitative measures, i.e., carbon footprint, cost savings, material efficiency use, and energy efficiency [3]. These measurable outcomes are used most frequently as part of a misguided effort to create a justification case for smart technology investment and also to benchmark operating and environmental performance against.

In real-life situation, sustainability is far beyond what is achieved through technology alone according to the triple bottom line of environmental, financial, and social issues. An imbalanced and disproportionate emphasis on measurable performance does make a person shortsighted to quantitative performance like enhanced workers' welfare, job enrichment, worker decision-participation, organizational cultural change, and socio-technical integration. For example, as a stepping stone to this, a factory maximizes energy use with AI in such a manner that it maximizes, and in so doing, it also maximizes the job stress, workers' alienation, or deskilling of the workers a consideration which the digital transformation analytics and sustainability reports barely reflect.

This quant-qual imbalance is a serious limitation of current empirical studies on implementing sustainable IR4.0/5.0. The result is a disconnected picture of sustainability performance with technology and environment concerns taking over the center at the expense of people- and social-focused concerns that are central to IR5.0 vision.

In addition, techniques used in the majority of empirical studies are not mixed methods techniques and therefore do not allow subjective, experiential, and context-dependent knowledge to be used to make decisions regarding how technological deployments affect different stakeholders [4], [5]. Leaving out such knowledge can potentially create policies and strategies that are short-term optimized but not aimed towards long-term objectives of sustainability like long-term worker satisfaction, civic participation, and optimized usage of technology.

Furthermore, empirical data for emerging markets as well as geographies that remain underrepresented to date are chiefly absent, lending further to smaller generalizability and scope of research results [6]. Such geographies generally are burdened with characteristic challenges such as infrastructural deficit, scarcity of skills, and regulative voids which have implications for IR4.0/5.0 success in implementation as well as in sustainability. Qualitative work by such contexts thus may not adequately consider realities on the ground nor offer practical, context-based solutions in analyses of sustainability.

Sustainability performance measurement needs a fundamental change due to the Industry 5.0 agenda. The automation and data-driven for productivity of IR4.0 stands opposite to IR5.0 which focuses on creating synergies between humans and machines for technology-based human capability enhancement rather than human replacement [7], [8]. Performance evaluation requires a transformation which should introduce metrics that care for people through assessments of mental and physical health as well as work-life harmony and social network development together with information technology literacy and job satisfaction levels.

The need for a paradigm transition receives more support every day yet scientists have not established adequate methods to measure how these softer metrics can be evaluated. Advanced supply chain management systems using algorithms and technologies perform excellent management tasks but we lack substantial research about how these systems influence employee attainment of purpose and creativity and self-direction at work [9], [10]. Although robots and machine learning technologies automate hazardous tasks, they frequently create job loss and destroy valuable industrial experience which organizations do not measure in their sustainability KPIs.

The exclusion of qualitative aspects makes meaningless the sustainable integration approach of IR4.0 and IR5.0 models. Complete all-round maturity of decision supports faces inhibition which prevents policymakers along with managers and practitioners from reaching all-round sustainability performance outcomes. Research in the next wave will harmonize facts and subjective realities to develop these N-dimensional portrait decision aids about digital transformation effects.

Furthermore, qualitative and quantitative integration of sustainability results is as much a matter of strategy as methodology. As businesses face increasing pressure from regulators, investors, and customers to demonstrate themselves as responsible innovators as well as socially responsible, the ability to report on and monetize social and human-focused outcomes is a business asset. Using weaker empirical evidence would allow firms to execute sustainability investments as mere marketing ploys which yield financial profit yet sustain social misconduct and worker grievances.

According to Blunck et al. [11], future research on this subject must combine quantitative data evaluation of energy statistics and productivity metrics and emission reductions with qualitative ethnographic interviews and in-field observation of cases together with stakeholder research sessions. Research through mixed methods will enables the measurement of both direct impacts alongside explanations about methods and reasons and inclusion of the affected participants as well as influence from environmental context.

Special integrated tools for sustainability assessment should be developed according to priorities for use within IR4.0/5.0 environments. The adoption of multi-criteria decision tools will enable assessment of environmental sustainability together with economic and social objectives through complete stakeholder involvement at technology implementation stages. The adoption of full-scale sustainability effects becomes possible through new methods in the combination of S-LCA and digital ethnography and human-centered design thinking.

Recent empirical studies about sustainable development driven by Industry 4.0 and 5.0 come up short when examining actual realities. Research and practice about sustainability suffer from insufficient analysis because they measure results primarily through quantitative numbers yet lack qualitative assessment methods. This research study intends to address this issue by using empirical data with field observations to accomplish its sustainability performance evaluation objectives through an expanded research approach. The realization of IR4.0/5.0 technologies depends on this approach to achieve its complete potential by creating better and stronger industrial systems which support human values.

2 | Methodology

In order to address the research gaps presented above, this study has proposed a novel assessment approach that is based on the integration of quantitative assessment with qualitative methods for evaluating IR4.0/5.0 sustainability. The methodological structure comprises of four inter-connected elements which include.

I. Stakeholder-centric system definition and criteria elicitation

II. Social Life Cycle Assessment (S-LCA) coupled with digital ethnography

III. Human-centered design thinking for iterative refinement and feedback loops

IV. Multi-Criteria Decision-Making (MCDM) for integrated sustainability evaluation

Stakeholder-centric system definition and criteria elicitation

Relevant stakeholders such as workers, managers, policy-makers and environmental and community members and experts participate in defining sustainability criteria across Environmental (E), Economic (C), and Social (S) dimensions during the first stage. A combination of participatory workshops and Delphi technique was used to gather and arranges essential sustainability indicators (criteria) for priority identification. The indicators used in this regard include:

I. Environmental: It covers CO_2 reduction, energy savings, waste generation.

II. Economic: Return on Investment (ROI), cost savings, productivity

III. Social: The worker's well-being which stands alongside the principles of inclusion alongside job satisfaction within the social category.

Mathematically, this can be expressed as follows:

Let

$$X = \{x_1, x_2, x_3, , , , x_n\}, \quad (1)$$

where, $x_1, x_2, x_3, , , , x_n$ are the set of sustainability alternatives that is the different IR4.0/5.0 technologies and adopted strategies.

$$C = \{c_1, c_2, c_3, , , , c_m\}, \quad (2)$$

where, $c_1, c_2, c_3, , , , c_m$ are the criteria based on the triple bottom line of environmental, economic, and social dimensions

S-LCA coupled with digital ethnography

In addressing one of the gaps identified in this study, a blended S-LCA and digital ethnography approach is proposed to addressed the human-centered aspects of sustainability using qualitative approach, which several studies in the past has reported to be missing in most of the sustainability assessment in manufacturing. In this study, the UNEP guidelines to measure social performance has been adopted for the S-LCA approach and they include:

I. Worker rights

II. Health and safety

III. Community engagement

IV. Human development

Hence, in the implementation of the S-LCA for sustainability in the manufacturing environment the following impact matrix is used:

$$S_{ij} = \text{Score of social subcategory j for stakeholder group i.}$$

Overall social score:

$$S_{total} = \sum_{i=1}^{k} \sum_{j=1}^{l} w_{ij} * S_{ij}, \quad (3)$$

where, w_{ij} is the weight of subcategory j for stakeholder group i. For the Digital Ethnography part, data are collected through wearables and mobile tracking devises after due consultation and consent. The data are also collected through online forums, video interviews and through chatbots capturing real-time feedback. They are coded and mapped to the themes (e.g., well-being, inclusion, autonomy).

Human-centered design thinking integration

Data is obtained through design thinking organizations establish specifically for this purpose. Repeated contact with both users and stakeholders is established. The phases involve in the human-centered design thinking include:

I. Empathize, where ethnographic study and surveys are carried out.

II. Define, systematic use of stakeholder inputs which transform problems into new frames.

III. Ideate, users together with stakeholders work with each other to generate potential solution.

IV. Prototype, the development of IR4.0/5.0 models (such as cobot integration).

V. Test, pilot and gather feedback using both qualitative and quantitative instruments.

The MCDM model accepts feedback which leads to dynamic modifications of weights and preferences.

MCDM (AHP-TOPSIS-VIKOR Framework) for integrated sustainability evaluation

The study used the Analytic Hierarchy Process (AHP) method to prioritize each criterion and the TOPSIS for ranking the alternatives, while the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method is used for validating the results. The AHP enables decision-makers to compare criteria and calculate their relative weights. The AHP process consists of the following steps [12]:

Pairwise Comparison Matrix (PCM): Decision-makers compare each criterion to every other criterion and give numerical values to indicate their relative relevance. Let w_{ij} signify the weight given to criteria ii over criterion j.

Normalization: To guarantee consistency, normalize the PCM and calculate the priority vectors for each criterion.

Eigenvalue and consistency ratio: Determine the eigenvalue and consistency ratio to confirm the consistency of judgments. The resulting priority vector, given by $W = (w_1, w_2, w_n, \ldots, w_n)$, indicates the weights of the criterion.

However, for data collection and normalization, it involves gathering relevant data for each of the indicator and ensuring comparability across them. This may include translating qualitative data to quantitative scales and standardizing numerical data (*Eq.(3)*).

$$\text{Normalized Matrix}_{ij} = \frac{\text{Data}_{ij} - \text{Min}(\text{Data}_j)}{\text{Max}(\text{Data}_j) - \text{Min}(\text{Data}_j)}. \tag{4}$$

The TOPSIS method ranks variables (alternatives) based on their performance compared to ideal and anti-ideal solutions. The TOPSIS procedure includes the following steps:

I. Create the Decision Matrix (DM): Combine the normalized data into a DM, with each row representing an alternative technology and strategy and each column representing a criterion.

II. Identify the ideal and anti-ideal solutions: Calculate the ideal and anti-ideal answers to each criterion.

III. Calculate the euclidean distance: Find the distance between each alternative technology and strategy and the ideal and anti-ideal solutions.

IV. Determine the relative closeness to the ideal solution: Using the formula, calculate how near each alternative technology and strategy is to the ideal solution as in *Eq. (5).*

$$\text{RC}_i = \frac{d^-(\text{ideal})}{d^-(\text{ideal}) + d^+(\text{Anti} - \text{ideal})}, \tag{5}$$

where, RC_i represents the relative closeness of each alternative technology and strategy i to the ideal solution. $d^-(\text{ideal})$ is the Euclidean distance from each alternative technology and strategy i to the ideal solution, and $d^+(\text{Anti} - \text{ideal})$ is the Euclidean distance from each alternative technology and strategy i to the anti-ideal solution. The alternative technology and strategy i are then ranked based on their relative closeness to the ideal solution. Hybrid MCDM model integrates AHP and TOPSIS data to manage and evaluate the alternative technology and strategy i concerns in a manufacturing environment. This integration enables this study to examine the relative relevance of criteria (AHP) and the performance of the alternative technology and strategy i compared to ideal solutions (TOPSIS) in the decision-making process.

To collect data for the study, a Likert-style rating scale for future subjective assessments was proposed and it is shown in *Table 1*. This scale enables respondents to score the technologies against criteria in a consistent and standardized way.

Table 1. Proposed 5-point rating scale for data collection.

Score Range	Scale Value	Interpretation
65–69	1	Very Low Performance
70–74	2	Low Performance
75–79	3	Moderate Performance
80–84	4	High Performance
85–89	5	Very High Performance

3 | Results and Discussion

This study is focused on the evaluation and ranking of seven technology alternatives that are central to sustainability of the manufacturing environment through IR4.0 and IR5.0, these technologies which include; IoT, AI, CPS, and smart robots, digital twin technology and human-robot Collaboration (Cobots) are designated as Tech A to Tech G and are evaluated in relation to their performance on ten criteria. These criteria included CO_2 emissions, energy efficiency, cost, job creation, social well-being, environmental impact, human rights, fair wages, flexibility, and user experience (UX). The DM, which consist of the raw performance for each technology with respect to the criteria, is presented in *Table 2*.

Table 2. Raw DM for Tech A–G on 10 sustainability criteria.

Technology	CO_2	Energy	Cost	Jobs	Wellbeing	Impact	Rights	Wages	Adapt	UX
Tech A	85	88	65	75	78	70	80	83	79	82
Tech B	82	85	68	80	76	65	85	88	84	87
Tech C	88	86	70	78	82	76	89	87	86	89
Tech D	75	80	72	70	74	74	78	75	72	70
Tech E	80	84	74	73	75	81	84	82	81	83
Tech F	83	87	71	76	80	79	86	85	85	86
Tech G	86	89	67	77	79	77	83	86	83	85

In determining relative importance for each of the criteria, AHP was used to derive weights. Weights signify relative importance of each criterion to be used while making decisions toward sustainability. Developed weights are summarized in *Table 3*.

Table 3. AHP-derived weights for the ten criteria.

Criteria	Weight
CO_2 Emission (CO2)	0.12
Energy Efficiency (EE)	0.11
Cost Efficiency (CE)	0.10
Job Creation (JC)	0.10
Wellbeing Impact (WB)	0.10
Environmental Impact (EI)	0.10
Human Rights (HR)	0.10
Wages (WG)	0.10
Climate Adaptability (AD)	0.09
User Experience (UX)	0.08

With the weights added, the second step was to normalize the raw DM so that unit inconsistencies are removed and all values are on the same scale. The normalized DM is shown in *Table 4*.

Table 4. Normalized DM.

Tech	CO_2	Energy	Cost	Jobs	Wellbeing	Impact	Rights	Wages	Adapt	UX
A	0.3880	0.3885	0.3528	0.3748	0.3791	0.3540	0.3615	0.3743	0.3661	0.3719
B	0.3743	0.3752	0.3691	0.3998	0.3694	0.3287	0.3841	0.3968	0.3893	0.3945
C	0.4017	0.3797	0.3800	0.3898	0.3986	0.3843	0.4022	0.3923	0.3986	0.4036
D	0.3423	0.3532	0.3908	0.3498	0.3597	0.3742	0.3525	0.3382	0.3337	0.3174
E	0.3651	0.3708	0.4017	0.3648	0.3646	0.4096	0.3796	0.3698	0.3754	0.3764
F	0.3788	0.3841	0.3854	0.3798	0.3889	0.3995	0.3886	0.3833	0.3940	0.3900
G	0.3925	0.3929	0.3637	0.3848	0.3840	0.3894	0.3751	0.3878	0.3847	0.3855

This normalized matrix was subsequently multiplied with the weight obtained from the AHP model to construct the weighted normalized DM, indicating both relative performance of all technologies and relative importance of each criterion. This matrix is presented in *Table 5*.

Table 5. Weighted normalized DM.

Tech	CO_2	Energy	Cost	Jobs	Wellbeing	Impact	Rights	Wages	Adapt	UX
A	0.0466	0.0427	0.0353	0.0375	0.0379	0.0354	0.0362	0.0374	0.0330	0.0297
B	0.0449	0.0413	0.0369	0.0400	0.0369	0.0329	0.0384	0.0397	0.0350	0.0316
C	0.0482	0.0418	0.0380	0.0390	0.0399	0.0384	0.0402	0.0392	0.0359	0.0323
D	0.0411	0.0388	0.0391	0.0350	0.0360	0.0374	0.0352	0.0338	0.0300	0.0254
E	0.0438	0.0408	0.0402	0.0365	0.0365	0.0410	0.0380	0.0370	0.0338	0.0301
F	0.0455	0.0422	0.0385	0.0380	0.0389	0.0399	0.0389	0.0383	0.0355	0.0312
G	0.0471	0.0432	0.0364	0.0385	0.0384	0.0389	0.0375	0.0388	0.0346	0.0308

Using this weighted matrix, the TOPSIS procedure was utilized to make an assessment. TOPSIS identifies ideal and negative-ideal solutions, calculates each of the technologies' Euclidean distances from the ideal and negative-ideal solutions, and calculates a closeness coefficient. TOPSIS closeness coefficients and final rankings are reported in *Table 6*.

Table 6. TOPSIS scores and rankings for technologies A–G.

Tech	Score
Tech C	0.8106
Tech F	0.7531
Tech G	0.6980
Tech E	0.5987
Tech B	0.5514
Tech A	0.4981
Tech D	0.2672

The results from the TOPSIS model show that the highest relative closeness value (0.8106) was with Tech C, which is the closest to the ideal solution, followed by Tech F (0.7531) and Tech G (0.6980) respectively. The three technologies excelled in comparison to most of the criteria and were the best runners. Technologies E and B were middling with closeness values of 0.5987 and 0.5514 respectively. These are quite strong performance-wise but there is room for improvement in areas like flexibility or cost.

Technologies A and D ranked lowest, of which Tech D performed worst in closeness with a value of 0.2672. This was because it had relatively low performance on a group of environments and social scores. To validate these results and obtain a compromise perspective, VIKOR method was also employed. VIKOR evaluates alternatives in terms of best group utility and lowest individual regret. S, R, and Q scores, and rankings are shown in *Table 7*.

Table 7. VIKOR scores (S, R, Q) and rankings for technologies A–G.

Tech	Q (Score)
Tech C	0.0000
Tech F	0.0876
Tech G	0.3272
Tech E	0.4925
Tech B	0.5492
Tech A	0.6179
Tech D	1.0000

Comparable to TOPSIS, Tech C was best in VIKOR (Q = 0.0000), again proving itself to be the most optimal and balanced option. Tech F (Q ≈ 0.0876) and Tech G (Q ≈ 0.3272) followed next, both again being part of the upper-class category. For the middle-class options, Tech E and Tech B were found to have a ranking of ~0.4925 and ~0.5492 for the with Q values respectively. Tech D, again for the second time, was at the bottom (Q = 1.000), again confirming itself as a poor performer. From the results and comparative analysis above, the following can be deduced recommended;

I. High correlation between TOPSIS and VIKOR rankings confirms good judgment. The first three top technologies (Tech C, F, and G) were consistently ranking high in a number of the sustainability factors and are to be given top priority for adoption or investment.

II. Tech C, for example, was the best in terms of the reduction of CO_2, energy usage, and social aspects like fair compensation hence its suitability for programs that focused on sustainability.

III. Tech F and G were also favorable through their affordability and versatility attributes.

IV. On the other hand, Tech D was below-average performance on the majority of the criteria including UX, hence deserves to be remove now and reconsider in the future. Tech A has a lower-middle ranking; hence it can be suggested that it should be considered for upgrading rather than direct use.

The succeeding ranking scheme is briefly presented in *Table 8* and provides comparative rankings for all the technologies for both methods.

Table 8. Comparative rankings of technologies using TOPSIS and VIKOR.

Tech	TOPSIS Score	Tech	VIKOR Q (Score)
Tech C	0.8106	Tech C	0.0000
Tech F	0.7531	Tech F	0.0876
Tech G	0.6980	Tech G	0.3272
Tech E	0.5987	Tech E	0.4925
Tech B	0.5514	Tech B	0.5492
Tech A	0.4981	Tech A	0.6179
Tech D	0.2672	Tech D	1.0000

4 | Conclusions

In this paper, attempt has been made to bridge the current research gap by addressing the increasing demands for the use of scientific and evidence-based approach to analyze the industry 4.0 and 5.0 technology based on its socio-economic as well as environmental sustainability. Despite the global popularity of the so-called emerging digital technologies such as AI, IoT, Big Data analytics, and CPS, studies have it that a wide gap still exists in MCDM analysis and exhaustive quantification of their impacts on sustainability along more than one dimension.

In order to address this issue, an integrated MCDM model which include, AHP and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and then cross-validated using the application of the

VIKOR methodology was proposed. The ten of the following criteria were applied which were adopted as key to the sustainability criteria—CO_2 emissions, energy efficiency, cost efficiency, job creation, wellbeing, environmental impact, human rights, fair wages, climate adaptability, and user experience—to assess in detail the performance of seven emerging technologies (Tech A to Tech G) for different Industry 4.0 and 5.0 configurations.

Weights were assigned to all of the criteria based on their relative significance using AHP. For instance, CO_2 emissions were assigned a highest weight of 0.12, then energy efficiency with a weight of 0.11, and others equally weighted such as cost, jobs, wellbeing, and impact each with a weight of 0.10. These were based on expert opinion of increasing environmental and human-centered issues in future industrial revolutions. The decision-making process was begun by developing a DM from the simulated data of the actual performance scores for all the criteria for all the technologies. It was normalized and multiplied with the AHP weights developed to achieve the weighted normalized DM. It helped in having a balanced comparison of all the alternatives by equating different units into the same scale as well as relative importance of every criterion.

The application of TOPSIS method allowed to determine closeness to a best solution (minimum cost, maximum benefit) for every technology and rank technologies in a decreasing order. The first place went to Tech C (0.8106), i.e., the improved composite sustainability performance. It was replaced by Tech F (0.7531), and then it was Tech G (0.6980). Technologies E (0.5987) and B (0.5514) were at midstream levels, while Tech A (0.4981) and Tech D (0.2672) were at lagging positions, which implies where they have to improve.

To ensure TOPSIS stability results, VIKOR was utilized. VIKOR, working with ranking and compromise solutions, also provided Tech C as the optimal technology with the value of 0.0000 (or optimal solution). Tech F (0.0876) and Tech G (0.3272) also gave better ranks, validating the analysis. Tech D achieved the maximum VIKOR value of 1.0000 and gave worst performance among the sustainability criteria utilized. The overlap of VIKOR and TOPSIS rankings of the results verifies the validity of the proposed decision model. More importantly, technologies such as Tech C, as being strict implementations of IR5.0 technologies with integrated AI, IoT, Big Data, and human-centered design, strictly performed better than others in environmental sustainability, socio-economic effect, and user experience.

Finally, the research could establish and verify a strong MCDM model for the analysis of nascent industrial technologies with regards to sustainability dimensions. The method is simple, replicable, and can be generalized for several industrial environments. The methodology enables decision-makers to classify technology in terms of cost-effectiveness, productivity and overall human and environmental worth which is central to IR5.0. The implications, therefore, involve imposing embracing holistic evaluation models so as to be in a place to push industries and policymakers toward more forward-thinking, sustainable, and equitable technological spaces. Future research can continue to evolve this model further in order to hone this model further with real-world evidence and the advice of experts and employ other Industry 5.0 technologies such as human digital twins and brain-computer interfaces with which it can continue to expand the boundaries of human-machine symbiosis in ecologically sustainable ways.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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