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Research article

A goal programming-based human-centric assessment model for Industry 5.0 supply chains: development and validation

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Abstract: This study responded to the need for practical and transparent assessment frameworks for Industry 5.0 human-centric manufacturing maturity. Current maturity models show two recurring limitations: arithmetic mean aggregation may mask critical weaknesses when high scores compensate for low scores across criteria, and equal weighting does not reflect expert judgments about the relative importance of assessment criteria. To address these issues, we have proposed the human-centric assessment model (HCAM), which integrates the best–worst method (BWM) weighting with min–max goal programming to generate expert-weighted and non-compensatory maturity levels. The HCAM operationalizes five dimensions, which are human–machine collaboration, workforce well-being, adaptive learning, ethical use of technology, and resilience, through 30 sub-dimensions derived from a systematic synthesis of the literature. In an empirical application to twenty firms, the optimization-based evaluation changed 42% of the maturity assignments compared to a simple average, indicating that the offsetting effects were substantial in the specific sample analyzed. The BWM comparisons showed acceptable consistency across the five dimensions (maximum consistency ratio = 0.038), and the instrument as a whole demonstrated moderate to acceptable internal consistency for an exploratory validation study (Cronbach's α = 0.693). Overall, the HCAM provides a rigorous and interpretable approach for assessing human-centric maturity.

Keywords: Industry 5.0; human-centricity; supply chain 5.0; best-worst method; goal programming; maturity assessment; manufacturing; compensation effects
Mathematics Subject Classification: 90B50, 90C29, 91B06

1. Introduction

The fourth industrial revolution was driven by automation through the integration of the internet, artificial intelligence, and cyber-physical systems. This paradigm, however, has been criticized for prioritizing speed and efficiency at the expense of worker well-being [1]. In contrast, Industry 5.0 puts humans back at the heart of production systems. It rests on three complementary pillars: a human-centered approach, sustainability, and resilience [2]. This perspective broadens the notion of value creation beyond profit alone to include social and human impacts [3, 4].

The transition to Industry 5.0 in industrial supply chains extends beyond individual companies. Indeed, manufacturing is at the heart of the supply chain; therefore, improvements to this process have a direct impact on the performance of all other activities in the chain [5]. Consequently, maturity assessments must go beyond mere internal digitization and include capabilities that foster resilience and collaboration throughout the chain.

Although Industry 5.0 places human well-being, resilience, and sustainability at the heart of industrial transformation, organizations still lack robust frameworks to assess their progress toward these goals [6, 7]. This transition requires assessment approaches capable of capturing human-centered capabilities as well as broader operational and organizational concerns [8]. This gap is particularly acute in manufacturing and supply chain sectors, where human-centric skills influence business continuity, workforce adaptability, technology governance, and coordinated decision-making. Existing maturity models have two significant limitations. First, many rely on arithmetic mean aggregation, allowing strong performance in some areas to offset critical weaknesses in others [9, 10]. Indeed, critical criteria regarding a human-centric capability may be masked due to the significant distortion of the maturity profile and although compensation is an accepted methodology in research on Industry 5.0, treatment of compensation as a design constraint is not considered most times. Second, they often assume equal weighting of all criteria, even though experts and organizations place varying levels of importance on human-centric skills depending on their strategic and operational context [11, 12].

To address these limitations, we present the human-centric assessment model (HCAM). This model is designed as an integrated maturity assessment model, composed of three elements. First, a conceptual framework defines the main dimensions and sub-dimensions of human-centered maturity in Industry 5.0. Second, a weighting system is used, based on expertise and using the best-worst method (BWM) to determine the importance of each criterion. Third, a non-compensatory aggregation and classification approach, based on min-max goal programming, allows for the assignment of maturity levels. The HCAM model is therefore neither a conceptual taxonomy nor an isolated technique, but a structured assessment model supported by complementary methods. HCAM's contribution does not lie in the isolated introduction of entirely new analytical techniques, since the BWM and min-max goal programming are well-established methods. Its novelty lies rather in the combination of these methods within a human-centered assessment architecture adapted to Industry 5.0. This architecture integrates a multidimensional conceptual framework, expertise-based weighting, and a non-compensatory maturity classification. To guide this study, the following research questions were formulated:

- Q1. How can the HCAM in Industry 5.0 supply chains be conceptualized using a structured, multidimensional assessment model?
- Q2. How can expertise-based weighting and non-compensatory aggregation be integrated into this model to improve the rigor and interpretability of the maturity classification?
- Q3. How does the proposed HCAM model perform when empirically applied to companies operating in different manufacturing sectors?

This study has six primary sections. Section 1 provides an overview of the study, its scope, and its unique research contribution, as well as defines the issues that the study will address. Section 2 will review existing literature within the scope of the study, as well as comparing existing models to that of the HCAM. Section 3 will provide a summary of the research approach utilized to build a research-based HCAM. It will also provide a description of the HCAM, including the five primary domains, sub-domains, and maturity levels associated with each primary domain. Section 4 will provide a summary of the research findings and discussion of the application and evaluation of the HCAM. The final section will provide a overall conclusion and summary of the overall impact of the HCAM, as well as ideas for future research opportunities.

2. Literature review

This section synthesizes relevant literature across three domains: maturity assessment models, multi-criteria decision-making methods, and goal programming optimization. Beyond the transformation of companies, recent research has highlighted the major implications of Industry 5.0 for supply chains and logistics systems. From this broader perspective, a human-centric approach is not only an internal organizational principle but also a skill that influences how companies adapt to the wider demands of the value chain, particularly in terms of resilience, continuity, adaptive learning, and the responsible use of technology. This perspective aligns with the emerging discussions on Supply Chain 5.0 and Logistics 5.0, which extend the principles of Industry 5.0 to inter-organizational and networked contexts.

2.1. Maturity assessment models: critical review

Industry 4.0 maturity models use technology as the key deciding factor and view human aspects of Industry 4.0 as secondary factors [6]. Recent efforts to adapt these models for Industry 5.0 still reflect these limitations, despite growing recognition of the need for human-centric and resilient supply chains [3, 13].

The fuzzy-rule-based maturity model developed by Bajić et al. [11] provides a model for measuring and assessing three pillars of Industry 5.0, which include non-crisp-based readiness outputs that address the uncertainty of human and social factors. Mladineo et al. [7] developed an Industry 5.0 model based on an index of Industry 4.0 while providing additional information about alignment with three Industry 5.0 pillars with the goal of providing Croatian manufacturing industry analysis. This limitation is consistent with the evidence from recent studies showing that many existing maturity models do not yet fully take into account the human-centric requirements of Industry 5.0 and remain heavily influenced by the logic of Industry 4.0 [14].

The strategy devised by Skėrė et al. [10] offers a framework for multicriteria evaluation consisting of ten criteria under the three pillars of Industry 5.0 while providing an A-to-E categorical grading scheme to evaluate industries. Furthermore, while some extended digital maturity models have begun to incorporate socio-technical dimensions [15], and roadmapping approaches have been proposed to guide digital transformation [16], few address the non-compensatory and ethically grounded assessment required for true human-centricity. Moreover, although the evolution of the human role is acknowledged [17], and workplace ergonomics and well-being are increasingly highlighted [18], these aspects remain fragmented in current assessment frameworks. These frameworks suffer critical limitations. Abril-Jimenez et al. [6] pointed out that most current key performance indicator (KPI) frameworks do not consider the role of human workers as contributors to the successful adoption of digital technologies. Resende Alves et al. [1] indicated a lack of clarity regarding the human-centric constructs measured in measurement tools for Industry 5.0. Despite growing interest in Supply Chain 5.0 and human-centric logistics, existing maturity models remain largely technology-driven or lack a clear aggregation logic [19]. This results in a methodological gap in assessing human-centric maturity, where a company's capabilities contribute to supply chain resilience and performance.

Relatively few Industry 5.0 models account for the impact of compensation as a design issue. Despite the use of fuzzy rules and categorical grading schemes to measure human-centredness, very few of these models are guided by comparisons to compensatory aggregation [7, 10, 11]. This lack of accountability highlights the need for the HCAM's contribution to Industry 5.0 methodologies.

Existing maturity models have largely contributed to operationalizing the concepts of Industry 4.0 and, more recently, Industry 5.0, by translating abstract principles into measurable dimensions. Their main strength lies in their ability to provide structured diagnostic frameworks for organizational self-assessment and strategic benchmarking. However, several limitations remain. First, many models remain heavily focused on technology and pay little analytical attention to human dimensions such as employee well-being, ethical management, or resilience. Second, when human factors are included, they are often treated descriptively rather than integrated into a rigorous logic of weighting and aggregation. Third, a significant limitation of many existing maturity models lies in their aggregation logic. In this structure, high performance on one criterion can compensate for poor performance on another. This problem can also persist in fuzzy and categorical models. Such compensation is problematic in human-centered assessment, as key dimensions, such as worker well-being and resilience, should not be considered entirely interchangeable. Therefore, a non-compensatory aggregation logic is more appropriate for assessing human-centered maturity in the context of Industry 5.0. These limitations underscore the need for a more methodologically robust and explicitly human-centered assessment framework.

2.2. Best-worst method (BWM)

The BWM is a multi-criteria decision-making (MCDM) method introduced by Rezaei [20]. This method uses significantly fewer comparisons than analytical hierarchical processing (AHP) methods, while maintaining superior consistency rates. By using a reference-based comparison structure, the BWM provides higher consistency rates than traditional comparison processes, and enables real-time tracking of the quality of the judgement being rendered [21].

In Industry 5.0, Sharma and Gupta [22] used BWM to rank cognitive digital twin strategies together with interpretive Structural Modeling (ISM) and cross-impact matrix multiplication applied to classification analysis through the use of hybrid methodologies for multidimensional assessment. Beyond Industry 5.0, Ozceylan and Tanyas [23] demonstrated the application of hybrid maturity assessment models to complex sustainability-based operational systems and demonstrated the need for transparency and robustness when designing measurement procedures. To date, there are few systematic applications of the BWM to assess human-centric manufacturing systems, and the literature has identified a need for standardization in reporting aggregation rules for the application of all multicriteria decision-making methods to Industry 5.0 issues [10, 22, 23].

Among multi-criteria weighting methods, the BWM method is particularly well-suited to this study because it allows for structured weighting based on expertise while reducing the pairwise comparison burden. Compared to more comparison-intensive methods such as AHP, the BWM method requires fewer judgments, which is especially important when the framework includes multiple dimensions and sub-dimensions, and when the expert panel is small. This reduced opinion-gathering burden helps improve the quality and consistency of responses while preserving their interpretability through explicit consistency checks. However, the BWM method remains dependent on the quality of expert selection and the clarity of criterion definitions, and its results can be sensitive to unstable or poorly specified preferences.

2.3. Goal programming and compensation elimination

Min-max goal programming is one method used to address multiple objectives through minimization of deviations from defined goal targets. In this method, the maximum deviation across all analyzed objectives must be minimized. This ensures that no one objective dominates the solution, and that performance across all objectives is balanced.

The choice of min-max goal programming in this study is based on its suitability for assessment problems where balanced development across dimensions is preferable to high average performance accompanied by critical weaknesses. This method minimizes the maximum weighted deviation from target levels, making the assessment more sensitive to the most critical deficiency in the profile. In this sense, the method does not represent a purely additive logic, but rather an aggregation rule aimed at finding a balance and providing moderate compensation. This property is particularly relevant in human-centered assessment, where major deficiencies in some areas should not be neutralized by high performance in others. The goal is not to claim that only the lowest-performing dimension matters, but to ensure that significant weaknesses remain visible in the final maturity classification. Therefore, min-max goal programming was chosen because it best reflects the precautionary approach required for human-centered Industry 5.0 assessment.

No previous study has combined expertise-based MCDM weighting with min-max goal programming in the literature for assessing Industry 5.0 maturity. Several authors have argued there is a need to move from descriptive scoring to prescriptive optimization, which will suggest improved allocation of resources or improved plans of action [10,11]. The lack of existing research indicates that the concept of MCDM via the BWM through min-max goal programming represents an innovative addition. However, this method can also lead to more conservative maturity classifications than additive approaches. Its results can be sensitive to the specification of objectives, constraints, and criterion weightings, and its logic may be less intuitive for readers unfamiliar with optimization-based decision models. Therefore, this method is particularly well-suited when the assessment objective is to identify balanced skill development and avoid overestimating maturity in the presence of critical weaknesses.

2.4. Research gap synthesis

Four integrated gaps have been identified within literature analysis as the basis for this research:

- Although averaging aggregation has been established, there are no explicit methods regarding compensation effects within the published literature.
- No documented BWM-goal programming hybrids exist, although authors advocate for prescriptive optimization of MCDM.

- There is an overall lack of validated standards for human-centric metrics that are used in studies and ongoing calls for standardized indicators.
- Although previous studies have proposed maturity frameworks for Industry 5.0, the literature lacks integrated models combining human-centered dimensions, expertise-based weighting, and non-compensatory aggregation within a single assessment structure.

The literature highlights a twofold gap. Conceptually, existing maturity models do not sufficiently integrate the human dimension of Industry 5.0 [24]. Methodologically, available approaches often lack a robust combination of expertise-based weighting and non-compensatory aggregation. These shortcomings justify the development of the HCAM, which aims to provide a more explicitly human-centered maturity structure and a more rigorous assessment framework. In fact, the HCAM develops methods for determining integrated BWM weighting with min-max goal programming optimization of the human elements of optimization and applies the techniques within a validated multi-dimensional framework for the manufacturing supply chain.

3. Methodology

From an operational point of view, the HCAM combines a conceptual maturity structure with expertise-based weighting and optimization-based maturity classification in a unique integrated assessment logic. To implement this integrated logic, a structured research design was adopted. In fact, this study follows a four-phase research methodology (Figure 1), progressing from conceptual development theory to mathematical formulation, empirical validation, and statistical validation. The qualitative views of experts in this field have been combined with quantitative data using mathematical methods to ensure that findings are useful in practice and that our methodologies are valid.

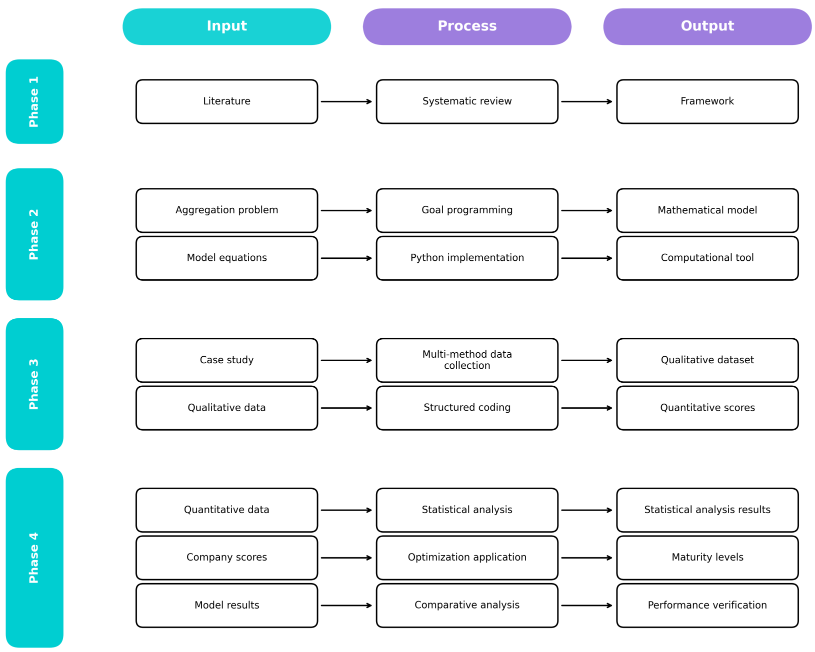

Figure 1. Overall research design.

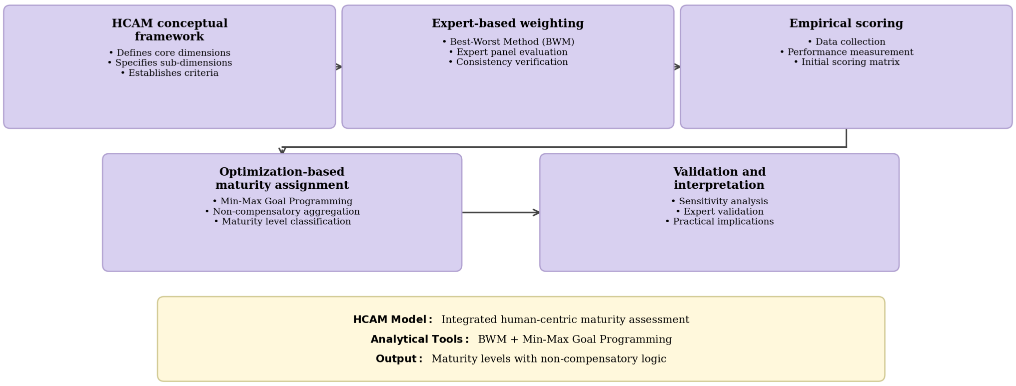

Figure 2. Operational logic of the HCAM.

While Figure 1 presents the overall research design of the study, Figure 2 summarizes the internal operational logic of the HCAM, distinguishing the conceptual framework from the weighting, scoring, classification, and validation procedures used to implement it.

3.1. Phase 1: Framework development

Table 1. HCAM dimensions and their definitions.

Dimension	Abbr.	n	Focus Area
Human-Machine Collaboration	HMC	7	How the workers and intelligent systems cooperate effectively in order to enhance productivity while maintaining human control, safety, and trust from isolated automation toward adaptive, shared workspaces [1, 25, 26].
Workforce Well-Being	WWB	6	The organization's dedication to safeguarding and improving employees' physical and psychological health across preventive and supportive practices such as ergonomics, safe work design, and systematic risk management [6, 18, 27, 28].
Adaptive Learning	AL	7	The organization's ability to support continuous learning in order to adapt the employees' skills to the changing technologies and work requirements through training, competency development, and knowledge sharing [26, 29–31].
Ethical Use of Technology	EUT	5	The extent to which digital technologies are developed and deployed according to ethical principles, such as transparency, fairness, and respect for human dignity, so that performance gains do not come at the expense of human rights or equitable access [1, 4, 22].
Resilience	RES	5	The organization's capacity to anticipate, absorb, adapt to, and recover from disruptions while maintaining human-centric priorities along flexible processes, learning-oriented recovery, and prepared teams [4, 7, 27].

Through a systematic review of the literature, the research identified recent developments on the application of Industry 5.0, human-centered manufacturing, and maturity models between the years 2015 to 2025, and specifically paid attention to the emerging practices of Industry 5.0 implementation. A thematic approach coupled with expert consultation led to an analysis of the core elements of each aspect of human-centricity, which made up the 5 dimensions of the framework listed below. Collectively, these elements provided the basis for the HCAM framework and informed the formulation of the model developed in Phase 2. The proposed framework contains 5 dimensions, represented as 30 different sub-dimensions, which can be found in Appendix A.

The assessment of maturity, as defined in the literature [32–36], has been developed into five distinct levels of maturity. Appendix A outlines each of the five maturity assessment levels.

3.2. Phase 2: optimization model formulation

The second phase focused on developing the mathematical optimization model to address identified limitations in conventional assessment approaches.

3.2.1. BWM for weight calculation

The BWM method was used as a structured method to determine the relative importance of the criteria considered in this study. The weighting stage relied on a targeted panel of four experts with relevant knowledge of Industry 5.0, production systems, and human-centered organizational practices. These experts were selected based on their familiarity with the conceptual dimensions of the framework and their ability to assess the relative importance of the proposed sub-dimensions in industrial contexts. Using the BWM procedure, each expert independently compared the sub-dimensions of each HCAM dimension by identifying the most and least important criteria (Appendix B, Table 6) and then ranking preferences (from best to worst) on a scale of 1 to 9 [23]. These comparisons allowed for the establishment of local weighting vectors for each dimension. Consistency ratios were calculated for the five dimensions using the BWM optimization model proposed by [20]. Table 7 in Appendix B presents the consistency statistics for all 20 expert–dimension combinations. All consistency ratios fall well below the threshold of 0.2, ranging from 0.011 to 0.038, confirming high reliability of the expert judgments. Only consistent judgments were retained, and the final combined weighting vectors were obtained by taking the geometric mean of the experts' individual weighting vectors (Appendix B, Table 8).

3.2.2. Min-max goal programming

To eliminate compensation effects, a gap noted in existing frameworks [10, 11], this study employs min-max goal programming. Unlike traditional approaches that allow high scores in one dimension to cancel deficiencies in others, min-max optimization selects the maturity level that minimizes the maximum weighted deviation across sub-dimensions.

Sets and Indices

S: Set of sub-dimensions within the dimension, indexed by $s = 1, 2, 3, 4, ..., n$.

Parameters

- $a_s \in \{0, 1, 2, 3, 4\}$: Assessed maturity score for sub-dimension s, obtained from empirical data collection (Phase 3).
- $w_s \in (0, 1]$: Importance weight for sub-dimension s, derived via the BWM, with $\sum_{s \in S} w_s = 1$.

Decision Variables

- $y \in \{0, 1, 2, 3, 4\}$: Integer maturity level to be assigned to the overall dimension.

- $d_s^+, d_s^- \geq 0$: Positive and negative deviation variables for each sub-dimension s, representing overachievement and underachievement relative to y.
- $D \geq 0$: Maximum weighted deviation (min-max objective).

Objective Function

$$\min D \tag{3.1}$$

We minimize the worst-case (maximum) weighted deviation across all sub-dimensions. This ensures no single sub-dimension is excessively misaligned with the final maturity level.

Constraints

Goal Definition Constraints:

$$a_s - y = d_s^+ - d_s^-, \quad \forall s \in S \tag{3.2}$$

This defines the positive (d_s^+) and negative (d_s^-) deviations of each sub-dimension score from the target level y.

Min-Max Constraints:

$$D \geq w_s \cdot (d_s^+ + d_s^-), \quad \forall s \in S \tag{3.3}$$

This forces D to be at least as large as every sub-dimension's weighted absolute deviation $w_s \cdot |a_s - y|$.

Integrality and Non-negativity:

$$y \in \{0, 1, 2, 3, 4\}, \quad d_s^+, d_s^- \geq 0, \quad D \geq 0 \tag{3.4}$$

Computational Implementation: The optimization model was implemented in Python utilizing the SciPy optimization library for linear programming solutions.

In its current formulation, goal programming is not used to evaluate performance against predetermined target values. Rather, it serves as a classification-oriented optimization procedure, where the maturity level y is a decision variable. The model selects the discrete maturity level that minimizes the maximum weighted gap between the observed sub-dimension scores and the maturity classification assigned to the dimension level. In this sense, the model's role is to determine the most appropriate maturity level for a given profile, rather than to measure the gap from a predefined target state.

3.3. Phase 3: Empirical data collection

In this phase, the theoretical framework is implemented through case study investigations, which utilized a variety of data collection techniques, including systematic coding protocols to align with the data collection methodology described in the recent literature on the successful implementation of Industry 5.0 [6, 26].

3.3.1. Case selection strategy

We validated the proposed HCAM through an empirical application involving twenty manufacturing companies (C1–C20) operating in two industrial contexts. The sample was structured into two groups to enable cross-sector comparison: automotive firms (C1–C10) and aerospace firms (C11–C20). This design allowed us to examine the model's applicability and consistency across different manufacturing environments, while ensuring balanced representation from each sector. Although the empirical application is conducted at the company level, the selected companies operate within industrial value chains where human-centric capabilities have implications that extend beyond mere internal performance. Therefore, the company is treated in this research as the primary unit of analysis through which Industry 5.0 maturity can be examined as a foundational enabler of broader supply-chain resilience, coordination, and continuity.

The case selection strategy prioritizes exploratory validation in two manufacturing sectors over statistical representativeness. We recognize that the sampled companies may differ in size, regional operating context, and regulatory exposure, all factors that can influence the adoption, formalization, and visibility of human-centered practices. Consequently, the cross-sector comparisons presented in this study should be interpreted as analytical and exploratory findings, not as generalizations to the entire population.

3.3.2. Data collection instruments

Data were collected through interviews (15–20 minutes) with managerial and HR roles, document analysis (policies, training and safety records, implementation plans), and on-site observation of human-machine interaction and work system design.

3.3.3. Structured coding (qualitative → quantitative)

Each sub-dimension was coded using a five-level maturity scale (0–4) to ensure consistent scoring across companies. Scores were assigned based on evidence from interviews, documents, and on-site observations.

3.4. Phase 4: Statistical analysis and validation

3.4.1. Optimization application

Each company's benchmark score was calculated by taking the simple arithmetic mean of its 30 sub-dimension scores, thus treating all sub-dimensions as having the same weight and being fully compensatory. The next step was to apply min-max goal programming to explore an optimization approach for evaluating companies while minimizing adverse weighting effects on the assessed criteria. The final analysis was a comparison of both the benchmark results and the optimization results via deviation analysis to identify any quantitative differences between both performance rankings and scores.

3.4.2. Statistical validation

The reliability of measurement items was assessed through Cronbach's alpha to establish internal consistency [37]. In accordance with standard practice in applied research, Cronbach's alpha values close to 0.70 were considered acceptable, while values close to or above 0.80 were considered good. Given the exploratory nature of this validation, values close to the 0.70 threshold were interpreted with caution, as they indicate moderate internal consistency [38]. A Pearson correlation analysis was used to explore the extent to which the five dimensions of the HCAM behave as interrelated components within a larger human-centered system [39]. This analysis was not intended to formally test discriminant validity, but rather to examine whether the dimensions exhibit a consistent pattern of interdependence while remaining conceptually distinct. Lastly, we compared the two outcomes of the simple average baseline and min–max goal programming models [40–42] as these models are commonly used to solve multicriteria decision-making problems where multiple objectives may conflict, allowing explicit control over deviations. Differences between the baseline and optimized results were analyzed to quantify potential compensation effects inherent in additive aggregation methods, using established MCDA insights on the behavior of simple additive weighting [43, 44].

4. Results

The HCAM framework was used to collect empirical data on two sectors of companies to obtain empirical results. The results obtained can be organized in an analytical order as follows: weight calculation, optimization comparison, reliability evaluation, and inter-dimensional correlation analysis.

4.1. BWM weight determination

The relative importance of the various components for each dimension was agreed upon by the experts. The aggregate weights for each dimension were based on the consensus opinion of the four experts. The HMC dimension had a highest priority, as shown in Figure 3, placed on Human-Centric Technology Design at 0.215, followed closely by Collaborative Robotics at 0.168, thus displaying a clear indication of what type of human-machine interaction will work effectively. Therefore, designing the technologies for humans' needs and work practices should begin during the design phase rather than waiting until after deployment to adjust via corrective actions.

According to Figure 4 within the WWB dimension, Ergonomic Improvement (0.239) and Health and Safety Programming (0.229) received the highest prioritization, indicating that safety from physical harm and having a healthy workplace environment are key components that make up a human-centric approach to work. Remote Work had the lowest weight of the three categories as this category has limited applicability based on the work context.

Experts assigned the highest ranking to Reskillling for Automation (0.203) and Just-in-Time Learning (0.202), thus highlighting the fact that organizations must provide employees with both proactive training prior to the implementation of automation initiatives and timely learning mechanisms to help them adjust to operational alterations. From the EUT perspective, Human Oversight ranked first (0.274) and Data Privacy (0.250) second, illustrating that experts believe the ethical application of technology is driven primarily by appropriate governance, accountability, and managerial controls. Concerning RES, the two sub-dimensions with the highest rankings were Flexible Workflows (0.264) and Redundancy in Skills (0.258), indicating that a resilient organization depends heavily on a flexible work structure and a highly skilled workforce that possesses transferable skill sets to weather disruptions. In order to preserve the readability of the main text, the detailed presentation has been limited to certain illustrative dimensions, while the complete set of sub-dimension weightings for all five HCAM dimensions is presented in Appendix C.

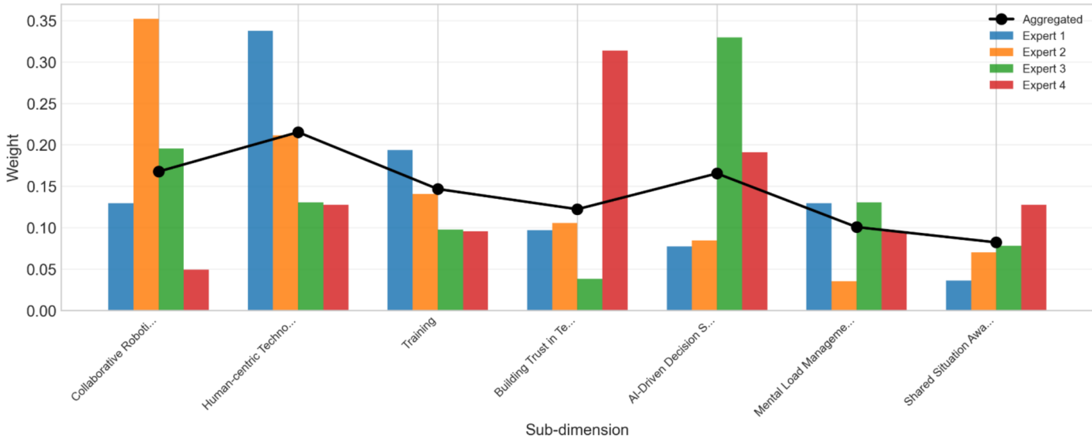

Figure 3. BWM weight distribution for HMC sub-dimensions.

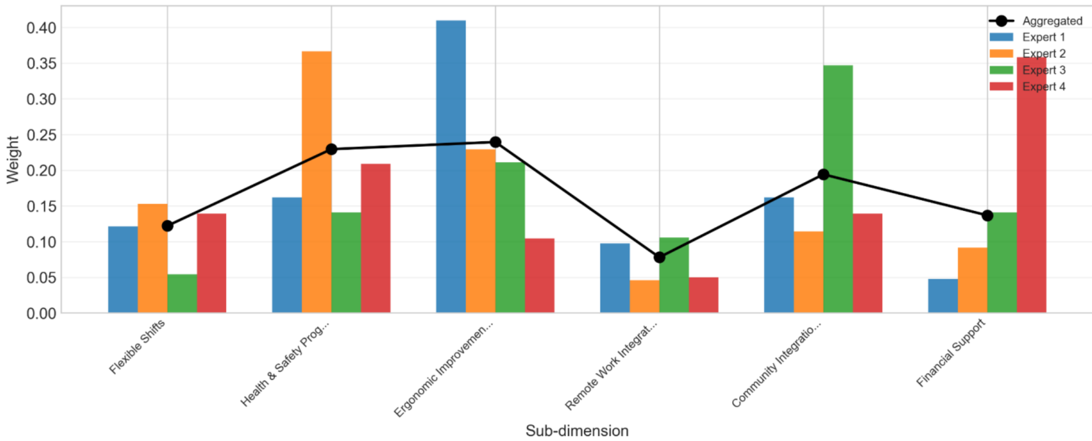

Figure 4. BWM weight distribution for WWB sub-dimensions.

4.2. *Comparative optimization analysis*

The optimization procedure changed the maturity classification of 42 out of 100 cases (42%). With a simple average, significant weaknesses remain masked because good performance in some areas compensates for shortcomings in others.

To formally assess whether the optimization produces systematically different maturity assignments compared to simple averaging, a Wilcoxon signed-rank test was conducted on the 100 paired observations (20 companies × 5 dimensions). The test revealed a highly significant difference between the two approaches ($W = 547.0$, $p < 0.001$), corroborated by a paired t-test ($t = -7.63$, $p < 0.001$). The optimized maturity levels ($\bar{x}_{\text{opt}} = 3.02$) were systematically higher than the simple average scores ($\bar{x}_{\text{avg}} = 2.68$), with a mean difference of +0.34 ($SD = 0.45$) and a large effect size ($r = 0.60$). Directional analysis showed that in 76% of the cases the optimized level exceeded the simple average: in 13% it was lower, and in 11% it remained unchanged. At the dimension level, WWB ($p = 0.001$), AL ($p = 0.009$), EUT ($p < 0.001$), and RES ($p = 0.038$) all exhibited statistically significant upward shifts under optimization, while HMC showed a non-significant trend ($p = 0.384$). Both sectors displayed significant effects: automotive ($W = 128$, $p < 0.001$) and aerospace ($W = 145$, $p < 0.001$). These results confirm that the min-max goal programming optimization produces meaningfully and statistically significantly different maturity assessments compared to simple averaging, underscoring the compensation effect whereby strong sub-dimension scores mask underlying weaknesses that the optimization procedure reveals.

To establish a more explicit link between weighting and optimization outcomes, the reallocation patterns observed for the five dimensions were interpreted in light of their aggregate BWM weightings. The comparison suggests that optimization outcomes are influenced not only by the importance assigned by experts but also by the empirical heterogeneity of company profiles within each dimension. Consequently, dimensions with the highest weightings did not necessarily exhibit the greatest number of maturity changes, indicating that weighting and reallocation frequency account for related but distinct aspects of the HCAM assessment process.

Figure 5 shows the automotive industry's diverse patterns of maturity based on company type. Companies classified as C1 and C2 have overall similar maturity profiles and did not demonstrate a significant change after employing our optimization process. In contrast, C3 through C6 demonstrate a unique compensation effect; although their average maturity scores appear acceptable through simple analysis, our optimization also demonstrated that these companies possess deficiencies that were not identified through the standard calculations.

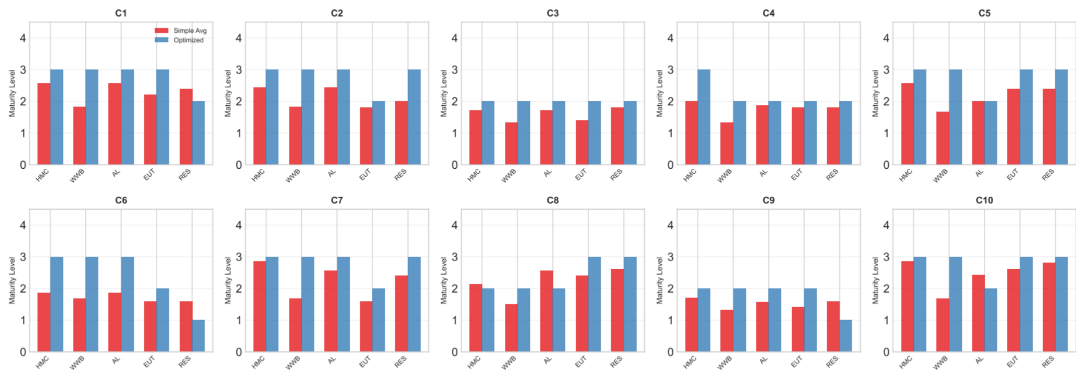

Figure 5. Simple average vs. optimized maturity levels: Automotive sector (C1–C10).

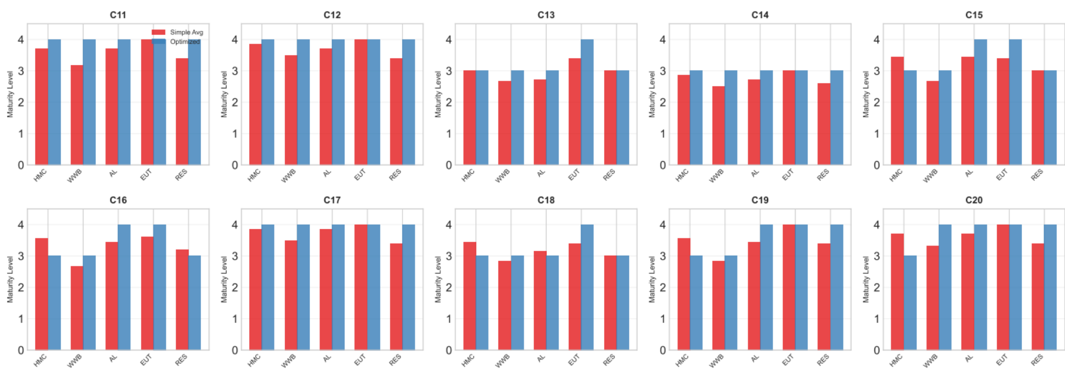

Figure 6. Simple average vs. optimized maturity levels: Aerospace sector (C11–C20).

Figure 6 indicates a different pattern of adjustment within the aerospace sector than any of the other sectors analyzed. Both of the leading firms, C11 and C12, had higher amounts of WWB and EUT after optimization than before. This shows that these two companies are governed better and operate using far more well-defined management practices than the remaining firms in the aerospace sector. On the other hand, companies C13–C17 displayed only moderate improvements following optimization when compared to the previous three aerospace sector firms. This indicates that these companies began with relatively equal profiles and had significantly fewer extreme weaknesses exposed by the optimization process.

4.3. *Cross-sector comparison*

In every area of human-focused practices across the five dimensions measured, aerospace establishments had a greater average score than their automotive counterparts as shown in Figure 7. The differences in the average scores were significant for each dimension and were greatest in EUT and AL.

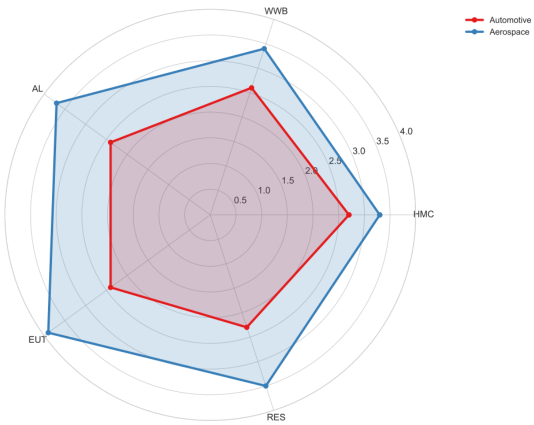

Figure 7. Sector average profiles: Aerospace vs. Automotive.

4.4. *Internal consistency assessment*

Cronbach's alpha coefficients were calculated to assess internal consistency within each HCAM dimension:

Table 2. Internal consistency assessment.

Dimension	Cronbach's α	Items	Interpretation
HMC	0.686	7	Moderate
WWB	0.553	6	Questionable
AL	0.904	7	Excellent
EUT	0.740	5	Acceptable
RES	0.583	5	Questionable
Aggregate	0.693	30	Moderate

The AL dimension demonstrated moderate internal consistency (α = 0.904), while the EUT dimension showed acceptable reliability (α = 0.740). The HMC dimension (α = 0.686) was slightly below the conventional threshold of 0.70, but remained moderate for an exploratory validation study. In contrast, the WWB (α = 0.553) and RES (α = 0.583) dimensions exhibited lower internal consistency.

These results suggest that the corresponding indicators may reflect conceptually broad and operationally heterogeneous organizational practices, rather than highly homogeneous latent constructs. Therefore, the results for these two dimensions should be interpreted with caution, and further refinement and validation of their conceptual structure are still needed.

4.5. Inter-dimensional correlation analysis

Pearson correlation coefficients were computed to examine relationships between HCAM dimensions, which are presented in Figure 8.

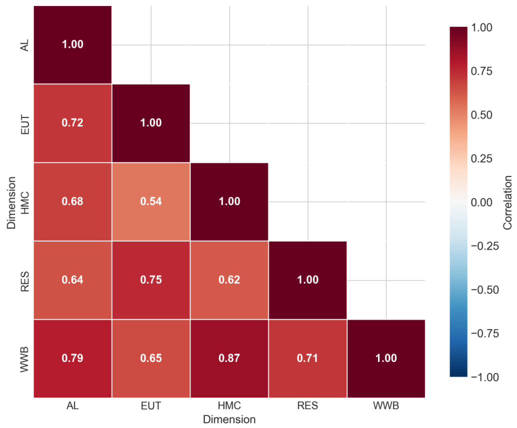

Figure 8. Pearson correlation heatmap showing inter-dimensional relationships.

The correlation matrix reveals consistently positive relationships among all five dimensions, with coefficients ranging from 0.54 to 0.87. The strongest association was observed between WWB and HMC (r = 0.87), followed by WWB and AL (r = 0.79) and RES and EUT (r = 0.75). The weakest, yet still moderate, correlation was found between EUT and HMC (r = 0.54). These results indicate that the five dimensions are positively correlated and may reflect interdependent aspects of human-centered maturity rather than entirely isolated capabilities. This observation supports the interpretation of the HCAM model as a coherent sociotechnical system, even though it does not in itself constitute a formal test of discriminant validity. In particular, the strong correlation between WWB and HMC suggests that these two dimensions may be closely related and exhibit partial empirical overlap in the sample studied. Future research should therefore more rigorously examine their empirical specificity using additional construct validation procedures.

4.6. Sensitivity analysis of BWM weights

A systematic sensitivity analysis was conducted in this study in order to assess the robustness of the maturity level assignments to variations in the weights derived from the BWM model. The weight of each sub-dimension was perturbed by ±10%, ±20%, and ±30% relative to its baseline value, with the remaining weights renormalized to maintain the unit sum constraint. For each perturbation scenario, the min-max goal programming optimization was rerun for all 20 companies and 5 dimensions, and the resulting changes in the maturity level assignments were recorded.

Of the 180 disruption scenarios tested (30 sub-dimensions × 6 disruption levels), 47 scenarios (26.1%) resulted in a change in the maturity level of at least one firm. The maximum impact of a single disruption was observed for WWB integration, where a weighting change of ±30% affected the maturity level of 45% of firms. Figure 9 presents a tornado diagram ranking all sub-dimensions according to their maximum impact on maturity level.

At the dimensional level (Figure 10), WWB exhibited the highest average sensitivity (9.9%), followed by RES and AL. EUT (3.2%) and HMC (1.1%), proved comparatively robust to weighting variations.

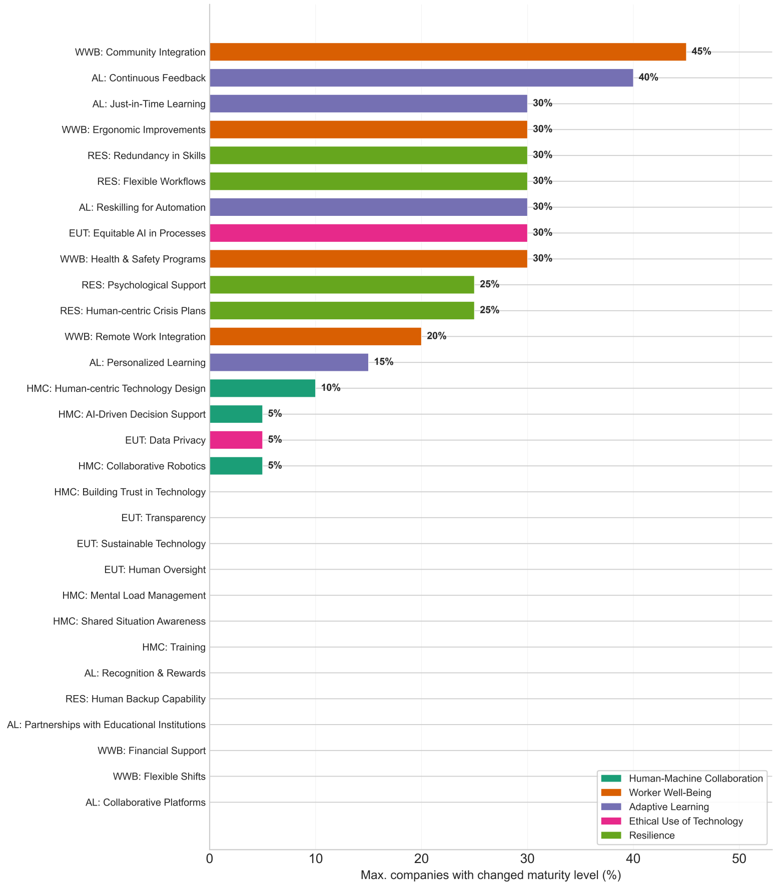

Figure 9. Sensitivity tornado chart: maximum percentage of companies with changed maturity levels per sub-dimension weight perturbation.

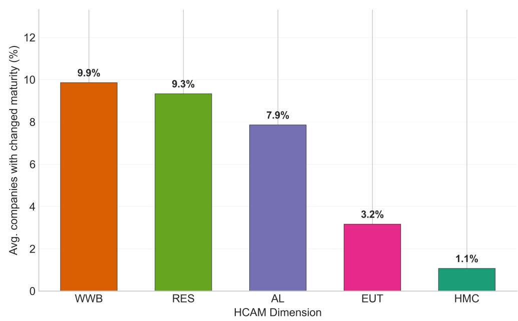

Figure 10. Average sensitivity by HCAM dimension: percentage of companies affected by weight perturbations.

These results show that, although the model reacts to significant changes in weighting in some sub-dimensions, the overall framework remains stable. Approximately 74% of the disruption scenarios resulted in no changes to the maturity assignments, indicating that the weightings derived from the BWM provide a solid basis. The sensitive sub-dimensions correspond to the areas where expert opinions exhibit the greatest variance, suggesting that targeted expert consultation could improve the accuracy of the weighting in these areas.

5. Discussion

This section interprets empirical findings within the broader context of human-centric manufacturing assessment, examining compensation effects, theoretical contributions, practical implications, and study limitations.

5.1. Methodological validation: compensation effect

The results of the evaluation based on optimization resulted in changes in the maturity classifications of 42 of the 100 dimension-company pairs. This indicates a considerable difference compared to the classification of maturity based solely on simple averages. This shows that using simple additive averages will frequently yield inaccurate results for a significant proportion of the cases analyzed due to the fact that strong scores in one dimension can often offset weak scores in another dimension. The biggest changes were seen in companies in both the automotive and aerospace industries, which generally have the most variations in terms of the distribution of performance across all dimensions being assessed. Thus, the combination of the HCAM and optimization produces a more diagnostic assessment in that it helps to uncover any underlying gaps that would not have been apparent through simple aggregation of data.

5.2. Supply chain implications of human-centric maturity

From a supply chain perspective, the observed differences in maturity suggest that human-centric capabilities influence more than just an organization's internal preparedness. Companies that excel in AL, EUT, and RES are generally better positioned to maintain coordination, absorb disruptions, and preserve the quality of decisions under operational pressure. Conversely, weaknesses in employee well-being or resilience can create vulnerabilities that affect continuity, responsiveness, and collaboration within interconnected manufacturing processes.

Accordingly, the HCAM model should be interpreted not only as an organizational diagnostic tool, but also as a relevant framework for supply chain-driven industrial transformation. In manufacturing networks, human-centric maturity can be considered a prerequisite for effective coordination between technological systems, operational processes, and human decision-makers.

5.3. Theoretical contributions

This framework aligns with the broader definitional components of Industry 5.0, which include human-centricity, sustainability, and resilience [3], and extends prior digital maturity models [15, 24] by introducing a non-compensatory, optimization-based assessment mechanism. In fact, this paper makes a number of theoretical contributions to the Industry 5.0 and sustainable operations management literature.

First, this study contributes to the operationalization of the human-centered approach in Industry 5.0 by translating a general conceptual principle into a structured and measurable multidimensional assessment framework. Previous work has already highlighted the need for a structured assessment of the human-centered approach in industrial supply chains and has emphasized the lack of standardized, quantitative, and implementation-oriented frameworks [8]. In parallel, recent studies have proposed maturity-based approaches to assessing the implementation of Industry 5.0 in industrial contexts, including within small and medium-sized enterprises [45]. Compared to existing approaches by Bajić [11], Mladineo [7], and Skėrė [10], the HCAM places greater emphasis on the human as the central evaluation logic and is distinguished by its integration of weighting from expertise and non-compensatory aggregation.

Second, by combining the BWM with a min–max goal programming formulation, we introduce a mathematically sound non-compensatory aggregation procedure for such a maturity assessment. This contribution addresses weaknesses of simple arithmetic averaging procedures, where strong performance in some areas can compensate for the weakness of other dimensions and thus feedback uninformed or negligent attempts. Additionally, the strong correlations between the five dimensions of the HCAM suggest that human-centered maturity in Industry 5.0 is not simply a set of isolated capabilities, but rather an interdependent socio-technical configuration. Progress in one dimension can reinforce progress in others: for example, employee well-being can foster adaptive learning and trust, while resilience may depend on ethical governance and human-machine collaboration. This systemic interpretation strengthens the HCAM's theoretical contribution by challenging approaches that consider the dimensions as independent or additive. The HCAM thus contributes to the literature by combining a multidimensional, human-centered framework with a non-compensatory structure, consistent with the systemic nature of the transformation to Industry 5.0.

Overall, the proposed and validated framework helps bridge theory and practice, and provides a basis for future research to quantitatively examine the drivers, outcomes, and evolution of human-centricity in industrial ecosystems.

5.4. Practical implications

For practitioners pursuing the transition to Industry 5.0, the HCAM provides a structured basis for diagnostic assessment and decision support. The HCAM serves as an assessment tool allowing organizations to measure their current level of human-centric maturity across the five dimensions. In addition, the integrated optimization function translates assessment results in a manner that allows them to help determine priorities by singling performance sub-dimensions where the greatest weighted gap exists relative to the target market maturity level. In fact, the HCAM serves as a diagnostic and prioritization tool for managers seeking to drive the Industry 5.0 transformation in a more targeted way. Rather than relying on simple average scores, the model identifies weaknesses specific to each dimension, which remain visible even when other areas perform well. This allows managers to prioritize interventions in the sub-dimensions with the largest weighted maturity gaps, particularly in areas such as employee well-being, ethical use of technology, and resilience, where critical deficiencies should not be masked by better results elsewhere. In this sense, the HCAM supports resource allocation not in a generic way, but by linking managerial priorities to the specific imbalance structure revealed by the assessed company profiles. Overall, the approach supports more coherent improvement planning beyond isolated initiatives, strengthening organizational resilience, ethical governance, and long-term competitiveness.

5.5. Strategic roadmap for maturity advancement

In addition to the assessment, the HCAM can guide organizations in planning their transition toward higher human-centric maturity. Table 3 provides a structured set of strategic actions for each dimension, corresponding to transitions between adjacent maturity levels (0→1 through 3→4). The proposed actions were formulated by linking the maturity-level gaps identified through the HCAM to the conceptual content of the dimensions and sub-dimensions concerned. For example, advancing in HMC begins with pilot projects and basic training (Level 0→1) and progresses toward adaptive collaboration and cross-line governance (Level 3→4). This roadmap enables managers to prioritize interventions, allocate resources effectively, and track progression systematically, thereby bridging the gap between maturity assessment and actionable improvement planning.

Table 3. Strategic actions for advancing human-centric maturity across HCAM dimensions.

Dim.	Level	Strategic Actions
HMC	0→1	Select initial use cases; Determine basic rules and allocate a pilot owner; Train operators briefly and collect feedback
HMC	1→2	Standardize work instructions and human/system responsibilities; Run formal risk assessment and safety validation; Introduce basic KPIs
HMC	2→3	Embed HMC in process design; Upskill supervisors on Human-robots collaboration design; Establish continuous improvement
HMC	3→4	Deploy adaptive collaboration; Scale governance and benchmarking across lines; Audit trust, autonomy, and safety periodically
WWB	0→1	Perform a baseline risk scan; Fix obvious hazards and create a reporting channel; Assign clear accountability for well-being actions
WWB	1→2	Implement standard procedures; Track core indicators; Document and harmonize practices across teams
WWB	2→3	Integrate well-being into planning; Use structured employee feedback with defined response mechanisms; Include well-being in management review
WWB	3→4	Adopt proactive prevention; Benchmark and replicate best practices across sites; Strengthen culture linked to well-being outcomes
AL	0→1	Identify priority skill gaps for current technologies and roles; Launch short practical training for immediate needs; Create a basic knowledge base
AL	1→2	Build a competency matrix and role-based training plan; Standardize onboarding and refreshers for key roles; Track training completion
AL	2→3	Embed continuous learning routines; Create communities of practice and formal knowledge transfer; Update training from data
AL	3→4	Implement personalized pathways and just-in-time learning support; Forecast future skill needs; Establish governance structures
EUT	0→1	Map high-risk technologies and data uses; Set minimum privacy and consent rules for deployment; Assign an accountable owner for ethical compliance

Continued on next page

Dim.	Level	Strategic Actions
EUT	1→2	Define policies and procedures (privacy, access control, transparency); Introduce basic impact checks before deployment; Document decisions
EUT	2→3	Integrate ethics into lifecycle; Engage stakeholders in reviews; Monitor fairness and worker impacts with periodic assessments
EUT	3→4	Continuous assurance; Benchmark and align to standards and best practices; Promote ethical leadership
RES	0→1	Identify critical disruptions and key dependencies; Define basic incident response roles and communication steps; Create minimal backup procedures
RES	1→2	Formalize continuity plans and recovery procedures; Introduce cross-training for critical roles; Run basic drills and document lessons learned
RES	2→3	Embed scenario planning and regular stress testing; Strengthen adaptive capacity; Protect human-centric priorities
RES	3→4	Implement anticipatory monitoring and early warning signals; Use structured learning loops; Benchmark resilience across sites

*Note: The proposed actions are derived from the HCAM assessment framework and the interpretation of maturity gaps. They constitute indicative managerial guidelines and may require adaptation to the context during their practical implementation.

5.6. Limitations and future directions

This study has several limitations that should be highlighted. First, the empirical validation is based on a relatively small sample of 20 companies, which, while favorable for an exploratory assessment, limits the statistical generalizability of the results. Furthermore, despite a balanced sample across two sectors, differences in company size, regional conditions, and sector-specific regulatory requirements were not modeled as control variables; however, these contextual factors could partly explain the observed differences in maturity between cases and sectors. The empirical application was also conducted within a specific national and industrial context, which may limit the transferability of the results to other countries or institutional environments. Second, the analysis relies on cross-sectional data and therefore provides only a snapshot of human-centered maturity, without accounting for organizational evolution over time. Third, the BWM weighting process relied on a targeted expert panel of four participants; while acceptable for an exploratory, expert-based study, the small panel size may reduce the robustness of the resulting weightings. Finally, reliability at the dimension level was uneven. Although the conceptual specification of WWB and RES was refined to improve the clarity of the constructs, the relatively low alpha values observed for these dimensions indicate that they still require empirical revalidation on larger samples.

Future research should build directly upon the findings of this study. In particular, the refined conceptual specification of WWB and RES now requires empirical revalidation on larger and more diverse samples. The strong interdimensional correlations, especially between WWB and HMC, also suggest the need for additional construct validation procedures to more rigorously examine the empirical specificity of the proposed dimensions. Furthermore, given that the reallocation effects observed in the optimization framework are based on a limited sample and an expert panel, future work should test the robustness of the HCAM model in broader industry and national contexts and under different weighting scenarios. Finally, the proposed optimization component could be extended to a dynamic, multi-period formulation to examine how organizations can sequence their interventions over time to address the specific maturity gaps identified by the model.

6. Conclusion

This study led to the development and validation of the HCAM, an integrated maturity assessment model for Industry 5.0 production contexts, with implications for supply chain-oriented industrial systems. By combining expertise-based weighting with non-compensatory classification, the HCAM addresses two common weaknesses in maturity assessment frameworks: the masking of critical deficiencies by compensatory effects and the assumption that all criteria are equally important.

Empirical results showed that maturity level assignments changed in 42% of cases (at the company level) when optimization-based aggregation was used instead of a simple average. This finding is important because it indicates that human-centered maturity in the manufacturing sector is often characterized by heterogeneous capability profiles, where apparent overall preparedness can mask significant weaknesses in areas such as well-being, resilience, or the ethical use of technology. The results also highlighted strong interdependencies between dimensions, suggesting that human-centered maturity is best understood as a coherent sociotechnical configuration rather than a set of entirely isolated capabilities.

In this sense, the main theoretical contribution of this study lies not only in quantifying the human-centered approach but also in demonstrating that the weighting and aggregation of maturity significantly influence the perception of mature performance. Specifically, the HCAM model offers organizations a more relevant diagnostic basis for identifying weighted skill gaps and prioritizing interventions in areas where simple averages can mask significant vulnerabilities.

Future research should build directly upon the results of this study by empirically revalidating the refined WWB and RES dimensions on larger and more diverse samples. It should also more rigorously examine the empirical specificity of highly correlated dimensions, test the robustness of the HCAM model under different weighting scenarios and in broader contexts, and explore dynamic extensions of the optimization module for longer-term maturity planning.

Author contributions

Saloua Mihoubi: Conceptualization, methodology, project administration, resources, validation, visualization, data curation, writing—original draft, writing—review and editing; Badr Eddine Goumih: Resources, data curation, writing—original draft; Touria Benazzouz: Conceptualization, validation, supervision, writing—review and editing, project administration.

Use of Generative-AI tools declaration

Generative AI tools were used solely to assist in language refinement, grammar checking, and improving clarity of expression during the manuscript preparation. All conceptual development, framework design, empirical analysis, and interpretation of results were conducted entirely by the authors. No AI tools were used for data analysis, methodological design, or generation of research findings.

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Conflict of interest

The authors declare no conflict of interest. Touria Benazzouz is an editorial board member for Journal of Industrial and Management Optimization and was not involved in the editorial review or the decision to publish this article.

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Appendix A: Conceptual framework of HCAM

Appendix A presents the final structure of the dimensions and sub-dimensions of the HCAM model. For WWB and RES, the formulation has been adjusted to clarify concepts and reduce overlap between different practices. These modifications constitute conceptual improvements that will require further empirical validation.

Table 4. Final structure of the human-centric assessment model (HCAM).

Dimension	Sub-dimension	Definition
D1: HMC	D1.1 Collaborative Robotics	Robots designed to work alongside humans in shared spaces with safety features enabling physical interaction and task sharing.
D1: HMC	D1.2 Human-centric Technology Design	Interface and system design prioritizing user experience, accessibility, and ergonomic considerations for diverse worker populations.
D1: HMC	D1.3 Training	Structured programs developing competencies for effective human-machine interaction, from basic operations to advanced ones.
D1: HMC	D1.4 Building Trust in Technology	Organizational practices encourage confidence in automated systems through transparency, reliability demonstrations, and participatory implementation.
D1: HMC	D1.5 AI-Driven Decision Support	Intelligent systems augment human decision-making with data-driven insights while preserving human oversight and accountability.

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Dimension	Sub-dimension	Definition
D1: HMC	D1.6 Mental Load Management	Designing systems to prevent information overload and reduce mental fatigue for operators, enhancing decision-making and reducing errors.
D1: HMC	D1.7 Shared Situation Awareness	Ensuring both humans and AI systems have a common, transparent understanding of the current state of operations and goals.
D2: WWB	D2.1 Flexible Work Arrangements	Work scheduling accommodates individual needs while maintaining operational requirements, supporting work-life integration.
D2: WWB	D2.2 Occupational Health & Safety Management	Comprehensive risk management through identification, engineering controls, and preventive measures for occupational health.
D2: WWB	D2.3 Ergonomic Work Design	Workstation and tool modifications optimizing human-environment to prevent musculoskeletal disorders and enhance comfort.
D2: WWB	D2.4 Work Accessibility	Organizational frameworks enabling effective telework through technological infrastructure, managerial practices, and social connection maintenance.
D2: WWB	D2.5 Social Inclusion	Promoting an inclusive community and strong connections among workers to avoid isolation and build support networks.
D2: WWB	D2.6 Employee Support	Providing resources and programs to improve employee financial security, reducing stress and improving overall focus and satisfaction.
D3: AL	D3.1 Personalized Learning	Educational approaches tailoring content and methods to individual learner characteristics, preferences, and performance data.
D3: AL	D3.2 Just-in-Time Learning	Knowledge delivery provides contextually relevant information precisely when needed for immediate task performance or problem-solving.
D3: AL	D3.3 Collaborative Platforms	Digital environments facilitate knowledge sharing, peer interaction, and collective problem-solving through community factors.
D3: AL	D3.4 Upskilling and Reskilling	Structured workforce development strengthening current skills (upskilling) and building new ones (reskilling) in response to changes.
D3: AL	D3.5 Educational Partnerships	Strategic alliances ensure curriculum relevance, facilitating knowledge transfer, and creating talent pipeline development.
D3: AL	D3.6 Continuous Feedback	Systematic mechanisms for ongoing assessment and improvement of learning initiatives based on performance data and learner input.
D3: AL	D3.7 Recognition & Rewards	Structured approaches acknowledging and rewarding skill development through formal and informal acknowledgment mechanisms.
D4: EUT	D4.1 Equitable AI in Processes	Systematic design and monitoring of AI systems to ensure fair, unbiased, and inclusive decisions in organizational workflows.
D4: EUT	D4.2 Data Privacy	Practices protecting personal information through technical safeguards, administrative policies, and respect for individual consent.
D4: EUT	D4.3 Transparency	Clear communication of how technological systems operate, make decisions, and impact stakeholders through accessible documentation.
D4: EUT	D4.4 Human Oversight	Governance structures maintaining meaningful human control, review authority, and intervention capability over automated systems.

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Dimension	Sub-dimension	Definition
D4: EUT	D4.5 Sustainable Technology	Selection and operation of technological systems minimizing environmental impact through energy efficiency and circular economy practices.
D5: RES	D5.1 Disruption Preparedness	Emergency protocols prioritizing worker safety, psychological well-being, and basic needs during operational disruptions.
D5: RES	D5.2 Skill Redundancy and Cross-function Readiness	Workforce development creates overlapping competencies across employees to ensure operational continuity during unexpected gaps.
D5: RES	D5.3 Human-centric Recovery Support	Mental health resources helping employees cope with stress, trauma, and anxiety during disruptive events.
D5: RES	D5.4 Adaptive Workflow Flexibility	Adaptable processes that can be rapidly reconfigured to maintain operations under changing conditions or resource constraints.
D5: RES	D5.5 Continuity Improvement	Strategic capacity to maintain operational continuity through human intervention when automated systems fail or become unavailable.

Table 5. Definitions of maturity levels in the HCAM assessment model.

Level	Label	Description
0	Absent	Human-centric principles are absent, with no practices supporting human–machine collaboration, workforce well-being, ethical technology use, or resilience.
1	Initial	Human-centric initiatives exist only in isolation, applied inconsistently with limited documentation and low organizational awareness, often relying on individual efforts.
2	Developing	Basic procedures and early monitoring are in place, but human-centric priorities are only partly integrated into core processes and strategies.
3	Integrating	Human-centric principles are integrated into routine workflows and decisions, supported by regular review and performance feedback, with technology used to strengthen autonomy, safety, and well-being.
4	Optimizing	Human-centricity is fully embedded, supported by advanced analytics and a strong learning culture that enables continuous improvement and innovation.

Appendix B: Detailed BWM results

This appendix provides the complete BWM results for methodological transparency.

Table 6. Best and worst criteria selected by each expert for each HCAM dimension.

Dimension	Expert	Best Criterion	Worst Criterion
HMC	Expert 1	Human-centric Technology Design	Shared Situation Awareness
	Expert 2	Collaborative Robotics	Mental Load Management
	Expert 3	AI-Driven Decision Support	Building Trust in Technology
	Expert 4	Building Trust in Technology	Collaborative Robotics
WWB	Expert 1	Ergonomic Improvements	Financial Support
	Expert 2	Health & Safety Programs	Remote Work Integration
	Expert 3	Community Integration	Flexible Shifts
	Expert 4	Financial Support	Remote Work Integration
AL	Expert 1	Reskilling for Automation	Recognition & Rewards
	Expert 2	Just-in-Time Learning	Educational Partnerships
	Expert 3	Personalized Learning	Educational Partnerships
	Expert 4	Continuous Feedback	Recognition & Rewards
EUT	Expert 1	Equitable AI in Processes	Sustainable Technology
	Expert 2	Human Oversight	Transparency
	Expert 3	Transparency	Sustainable Technology
	Expert 4	Data Privacy	Sustainable Technology
RES	Expert 1	Redundancy in Skills	Psychological Support
	Expert 2	Flexible Workflows	Psychological Support
	Expert 3	Human Backup Capability	Psychological Support
	Expert 4	Human-centric Crisis Plans	Human Backup Capability

Table 7. BWM consistency statistics (ξ and CR) for each expert and dimension.

	Expert 1		Expert 2		Expert 3		Expert 4	
Dim.	ξ	CR	ξ	CR	ξ	CR	ξ	CR
HMC	0.050	0.011	0.070	0.016	0.061	0.016	0.069	0.030
WWB	0.076	0.020	0.092	0.031	0.076	0.033	0.060	0.020
AL	0.055	0.018	0.070	0.019	0.055	0.018	0.043	0.011
EUT	0.069	0.019	0.088	0.038	0.062	0.021	0.062	0.021
RES	0.069	0.023	0.079	0.021	0.053	0.014	0.071	0.024

Table 8. Final aggregated BWM weights (geometric mean of four experts).

Dimension	**Sub-dimension**	**Weight**
HMC	Collaborative Robotics	0.168
	Human-centric Technology Design	0.215
	Training	0.147
	Building Trust in Technology	0.122
	AI-Driven Decision Support	0.165
	Mental Load Management	0.101
	Shared Situation Awareness	0.082
WWB	Flexible Shifts	0.122
	Health & Safety Programs	0.230
	Ergonomic Improvements	0.240
	Remote Work Integration	0.078
	Community Integration	0.194
	Financial Support	0.137
AL	Personalized Learning	0.159
	Just-in-Time Learning	0.202
	Collaborative Platforms	0.122
	Reskilling for Automation	0.203
	Educational Partnerships	0.064
	Continuous Feedback	0.185
	Recognition & Rewards	0.066
EUT	Equitable AI in Processes	0.249
	Data Privacy	0.250
	Transparency	0.161
	Human Oversight	0.274
	Sustainable Technology	0.066
RES	Human-centric Crisis Plans	0.251
	Redundancy in Skills	0.258
	Psychological Support	0.070
	Flexible Workflows	0.264
	Human Backup Capability	0.157

Appendix C: BWM weight distribution for sub-dimensions

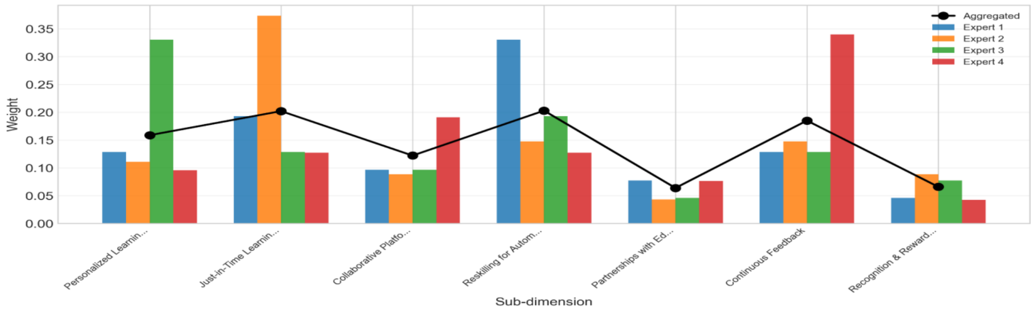

Figure 11. BWM weight distribution for AL sub-dimensions.

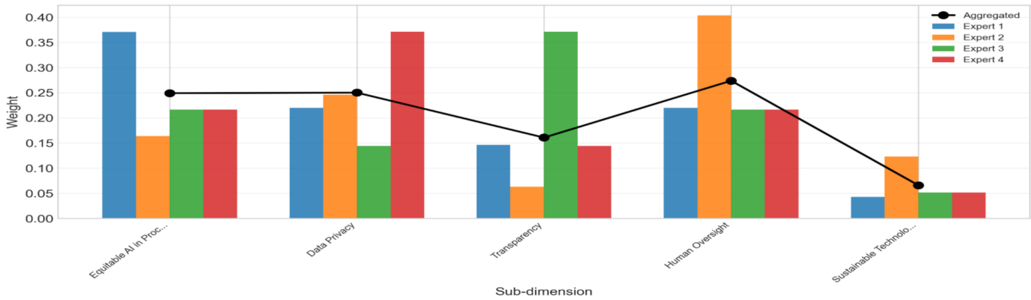

Figure 12. BWM weight distribution for EUT sub-dimensions.

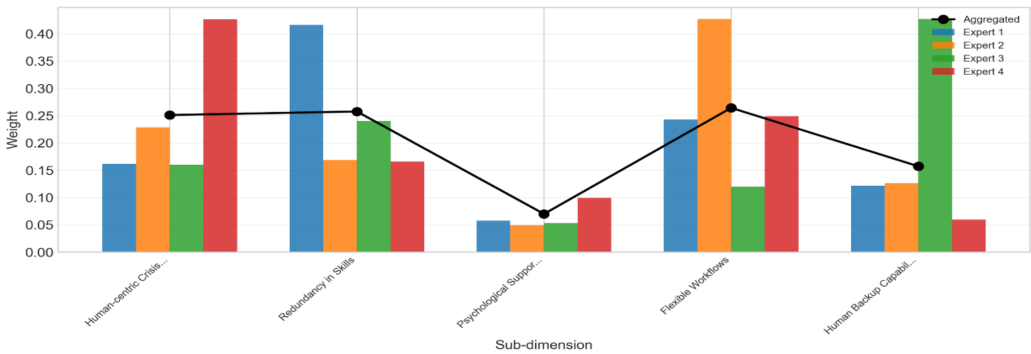

Figure 13. BWM weight distribution for RES sub-dimensions.