

# Human-Centered Model for Operational and Leadership Decision-Making in Corporate Nonlinear Environments

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**Abstract** - In recent years, the rapid pace of technology, especially in corporate environments, has accelerated the need for quicker and more efficient cognitive and structural adaptation of workers. The situation became more challenging by the fact that decision-making takes place under high uncertainty, and traditional linear models are no longer effective. Although existing research provides strong models and frameworks for digital transformation, a significant gap is still noticeable in integrating human cognition and technological output within the reasonable decision-making process across the board. This paper introduces the HTFusion Assessment – a human-centered operational and leadership model designed to close this gap. The proposed model outlines how system outputs can be converted into decisions and how responsibility is maintained during human-technology interactions. It also provides a structured approach to assess the costs of technological integration more precisely by integrating human and technology loss components, as well as the quality of leadership and the fairness and ethics scaling coefficients.

**Keywords** - HTFusion; operational model; leadership model; human-centered; technology adoption

## I. INTRODUCTION

In corporate ecosystems, rapidly developing technology is becoming harder for humans to adapt and within existing architectures. Corporations, which used to rely on human judgment, currently face difficulties in fostering decisions as the environment changes much quicker than the current setup allows. Therefore, new sophisticated tools have started to be used widely, even though alignment with existing systems is often conducted with the help of third-party solutions and automation, putting emphasize on automation of data integration [1]. Limiting the decision-making process to siloed data layers' availability automatically creates a challenge in the form of precision versus speed of the conducted analysis. With the emergence of artificial intelligence, the gap between human and technology interconnectivity has increased [4], making it difficult to address fast growing business demands, vast amount of data outputs being interpreted in a precise and timely manner.

The study found a lack of metrics to evaluate how effectively humans (workers) interact with systems. Those human-tech metrics could significantly contribute to estimating and interpreting such topics as operational risk, efficiency, or cost estimation. When humans do not

understand the algorithmic logic (the “black box” effect) [2], they most probably blindly trust the system (we can categorize that group of workers as “digital natives”) or reject it entirely (the category of “digital ignorants”), causing an increase in operational risk. If humans are willing to reduce the friction between legacy workflows and new technological interfaces, they fall into the “digital immigrants” group, which in the short-term decreases efficiency with an uncertain premise of increase in the long-term perspective [8]. Organizations frequently fail also with more tangible estimations like total cost of implementing new technologies, as they do not account for the cognitive load, retraining, structural realignment, as well as leadership quality or the fairness and ethics scaling coefficient.

## II. EXISTING APPROACHES

Literature research revealed a vast amount of well-thought approaches for technical adoption assessment. What is missing is a unified operational model for human-tech cognitive integration, while proposed frameworks remain fragmented, covering separately such topics as AI Governance, Digital Transformation Frameworks, or Leadership/Maturity models [5].

Most AI Governance models heavily rely on the concept of the “human-in-the-loop” to mitigate the risk of automation and ensure ethical compliance, leaving judgment part of the processes with humans [2]. However, research shows that this concept is overestimated as “cognitive offloading” when dealing with complex algorithmic outputs, is not taken into consideration. Evidence indicates that “human bias” (because of excessive trust in AI decision support) undermines operational safety and transparency [3]. In addition, the perception of automation as an ally lowers human “cognitive sovereignty”, which makes human oversight less effective and rather passive [4]. Overall, governance frameworks identify automation risks but lack operational measures such as intentional “friction points” to promote active human cognition.

In response to the shortcomings of pure automation, recent digital transformation strategies have shifted toward human-centered AI. Field studies show that customizing AI to match human cognitive styles increase the effectiveness of adoption and new technology usage. New models apply an approach focused on understanding how AI affects human well-being.

These approaches concentrate mainly on user-interface design and human-computer interaction [9]. None of those, though, explore how these human-centered designs influence distributed decision-making authority and systemic accountability [7].

In modern ecosystems, strategic adaptability is highly demanded. The third topic coming out of the research emphasizes that well-known traditional linear management approaches do not fulfill the needs of a dynamic environment. There is empirical evidence of nonlinear dependency between leadership and workspace stability, which requires the adaptation of a management team to real-time responses based on complex scenario analysis [6]. Despite these insights, current maturity models lack mathematical and operational measures to assess how the quality of leadership impacts the human-tech ecosystem.

In conclusion, current approaches do not define how system outputs can be translated into tangible corporate decisions, nor do they propose full operational cost measurements which consider human-tech interaction effectiveness and leadership/management decisions' impact. The HTFusion (Human-Tech Fusion) operational model is designed to fill this gap.

### III. ORGANIZATIONAL TRIGGERS FOR HTFUSION OPERATIONAL MODEL

In corporations where most of the processes are in place, systems are functioning, and data is being captured (we are not focusing on the effectiveness and quality aspect here, just on a fact of existence), indicators for HTFusion model implementation might be the following:

- Structural reorganization triggered by internal shifts.
- External regulatory requirements demanding higher compliance and auditability.
- Providers product capability or delivery methods changes.
- Strategy shifts toward emerging technology.

If some of those triggers appear, that would be the most appropriate moment for HTFusion model adoption; however, a baseline should first be established:

- Transformation goals and expected output are set and aligned with the business strategy.
- Current KPI's are validated for organization units' transformation plans, alignment to the overall organizational strategy, and delivery reports (delivery percentages, budget utilization, etc.).
- A technical ecosystem overview, focusing on departments with the highest recent IT spend, highest licenses usage, and most complex IAM login patterns, conducted.
- Workforce skillsets are analyzed with an emphasize on highest IT helpdesk ticket topics, upskilling programs, certificates, etc.

### IV. HTFUSION OPERATIONAL MODEL

The core contribution of this paper is the HTFusion Operational and Leadership model, which shifts the focus from 'what' the technology does to 'how' system outputs are reviewed, converted into decisions, and how responsibility is assigned and retained across human-technology interactions.

The HTFusion Operational model establishes whether lower than expected value generated by technology implementation stems from a human knowledge gap, or a technology implementation gap, crosschecked with the quality of leadership represented in a quantified way. It structures human and technology cognitive integration. It consists of the HTFusion Assessment, which is further used for HTFusion Index calculation, and the HTFusion Leadership model, which implies where human judgment or "friction points" are required and how to audit decision-making processes.

#### A. HTFusion Assessment

To ensure the HTFusion Operational model operates correctly, it must be continuously assessed. The HTFusion Assessment provides a clear procedure to establish data sources, prepare required data pipelines delivery, and agree on data end points. It also prepares tangible quantified measure for further interpretation within the model.

#### B. HTFusion Leadership model

The HTFusion Leadership model is a combination of human cognition and algorithmic output. In nonlinear environments, the need for feedback loop construction, cognitive human overload, and data analytics providing biased outputs creates an opportunity not just for managing people or managing IT, but to apply a more comprehensive approach. It defines leadership based on three pillars:

- Cognitive Sovereignty (the human aspect) – the ability to provide human judgment impacted by automation bias and cognitive overload. Leaders should design "friction points" to force critical thinking and introduce decision clarity by human reasoning.
- Algorithmic Accountability (the technology aspect) – the limitation of "black box" output acceptance. Leaders should establish clear rules to define to which extend technology (AI solution) is allowed to make autonomous decisions without human consultation.
- Dynamic Calibration (the fusion aspect) – the continuous adjustment of the approach based on environmental volatility. For any change, leaders check the current state and navigate next steps with human experts.

#### C. HTFusion Index

The core The HTFusion Index (HTFI) serves as a mathematical representation of the metric, which evaluates the health of the operational environment, including inputs from the HTFusion Assessment and HTFusion Leadership Model.

$$HTFI = [PV - (1 - Q)L_y - (1 - Q)L_z] \times HTFFE - C$$

Where:

PV – Projected Value of the technology implementation  
Q - Quality of HTFusion Leadership  
Ly - Losses due to human knowledge gap  
Lz - Losses due to technology implementation gap  
HTFFE - HTFusion Fairness and Ethics coefficient  
C - fixed costs

(Note: a detailed expansion of the HTFusion Index calculation with empirical validation of this formula will be explored in a separate paper).

## V. CONCLUSION

Rapid changes in emerging technology adoption have influenced drastically organizational environments, bringing a nonlinear aspect to traditional management structures. After multiple attempts at global digital transformation, most frameworks remain fragmented and the ambition to provide a “human-in-the loop” approach therefore is impeded. The produced paper demonstrates that creating a further gap between human and technology might cause a significant increase in operational risk, degrade decisions’ precision, and slow overall technology adoption.

To resolve this disparity, The HTFusion operational model was introduced, which shifts the organizational perspective from technology implementation towards conscious technology adoption. It operates on two approaches, which both contribute to the quantitative solution (HTFusion Index). The HTFusion Assessment focuses on data and processes preparation based solely on existing enterprise data sets. The HTFusion Leadership model provides a quantitative solution for leadership quality assessment. Both outputs contribute to the HTFusion Index, where decision-making process becomes quantitative for both technology and human aspects. HTFI calculates actual investment value taking into consideration technology correspondence with the organizational IT environment as well as human adaptability to the introduced or planned technology utilization. The HTFusion Operational model equips enterprises with measurements based on mathematical modeling (details of which will be explored more in further papers). It proves that technology adoption requires thoughtful and human-involved solutions and cannot rely solely on the technology aspect of implementation.

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