sdmimd
JOURNAL OF MANAGEMENT

DOI:10.18311/sdmimd/2026/56257

Human-Centred Narrative Intelligence in AI: Advancing Education and Training for Sustainable Manufacturing Leadership

C. R. Usha[1,2]

[1]Research Scholar, Karnataka State Open University, Mysuru – 570006, Karnataka, India

[2]Assistant Professor, Dayananda Sagar College of Arts, Science and Commerce, Bengaluru – 560111, Karnataka, India

Abstract

Narrative intelligence refers to the ability to create, interpret, and emotionally engage with stories. This study examines how computational narrative intelligence can enhance artificial intelligence systems through commonsense reasoning, multimodal learning, conceptual blending, and culturally grounded storytelling. The major findings indicate that enhanced AI narrative models demonstrate improved coherence, creativity, cultural relevance, and audience engagement when compared to baseline models. The study further suggests that computational narrative intelligence contributes significantly toward machine enculturation by enabling AI systems to better understand and internalize human sociocultural values.

Major Findings: Human-Centred Narrative Intelligence in AI enhances education and training by promoting critical thinking, ethical decision-making, and contextual understanding. It strengthens leadership development, learner engagement, and sustainability competencies while balancing technological innovation with human judgment for sustainable manufacturing.

Keywords: AI in Education and Training, Computational Storytelling, Decision-Making Transparency, Human-centred Artificial Intelligence, Narrative Intelligence, Sustainable Manufacturing Leadership

1. Introduction

The convergence of Artificial Intelligence (AI), education, and sustainable manufacturing leadership represents one of the most transformative frontiers of the 21st century. While AI has traditionally been seen as a computational and data-driven paradigm, the concept of narrative intelligence introduces a human-centred perspective. Narrative intelligence refers to the capacity of systems to understand, generate, and use stories for communication, interpretation, and decision-making. When applied to the training of manufacturing leaders, narrative intelligence can foster transparency, ethical awareness, and sustainability-oriented decisions. The urgency of embedding sustainability in manufacturing is undeniable, given the realities of climate change, resource scarcity, and economic volatility. At the same time, education systems must prepare leaders who can balance technological progress with human values and environmental stewardship. AI, enhanced with narrative intelligence, becomes a critical enabler in this transformation.

This research conceptualises human-centred narrative intelligence as a framework for strengthening leadership development. By incorporating storytelling practices, case-based reasoning, and explainable artificial intelligence, it attempts to close the divide between computational decision-making systems and human-oriented sustainable leadership models.

*Email: usha-bbabcom@dayanandasagar.edu

The importance of this study lies in its engagement with complex issues emerging at the intersection of artificial intelligence, machine learning, and human narrative traditions. Storytelling remains a core mechanism through which humans construct, transmit, and preserve cultural knowledge (Bruner, 1991). However, enabling machines to simulate narrative intelligence goes beyond surface-level pattern recognition; it necessitates commonsense understanding, cultural sensitivity, metaphorical interpretation, and creative reasoning.

The study further identifies key challenges such as limited domain-specific knowledge and the difficulty of processing metaphorical complexity, while also outlining promising directions such as large-scale textual corpora, crowdsourced knowledge systems, multimodal learning approaches, and conceptual blending techniques (Veale, 2017). Progress in these areas has the potential to transform sectors such as education, healthcare, entertainment, and human–computer interaction by enabling adaptive educational tools, culturally informed intelligent systems, and narrative-based therapeutic applications.

Ultimately, this research contributes to bridging computational models of narrative with the imaginative and meaning-making processes of human communication, moving AI closer to systems that can understand, empathise, and interact meaningfully.

2. Review of Literature

Storytelling, as a uniquely human cognitive and cultural practice, has long been examined across literature, psychology, philosophy, anthropology, and cognitive science. Jerome Bruner views narrative as a fundamental mode of thought through which individuals construct reality and organise experience (Bruner, J., 1986). Similarly, Walter Fisher's Narrative Paradigm conceptualises human beings as *homo narrans*, arguing that people understand the world through narrative coherence and fidelity. Narratives therefore function not merely as entertainment but as essential mechanisms for meaning-making, cultural transmission, and ethical reflection.

Research in cognitive science further demonstrates the significance of narratives in human cognition. Schank and Abelson (1977) contend that human understanding relies heavily on scripts, plans, and story structures that facilitate memory and interpretation (47-50). More recent studies on commonsense reasoning emphasise the importance of background knowledge and contextual understanding in human communication and decision-making (Davis & Marcus, 2015). These findings underscore the challenges faced by artificial intelligence systems attempting to replicate human-like narrative comprehension.

The development of computational narrative intelligence emerged from attempts to model storytelling processes computationally. Early symbolic approaches drew upon Vladimir Propp's structural analysis of folktales and David Rumelhart's story-schema theory. Subsequent research expanded into computational storytelling, narrative discourse modelling, and creative text generation (Finlayson, 2011). Gervás (2009) highlights the role of computational creativity in narrative generation, while Riedl identifies computational narrative intelligence as a central goal for creating human-centred AI systems capable of understanding and producing meaningful stories (Gervás, 2009; Riedl, M. O. 2016). Allen *et al*. (2010) demonstrated the practical application of computational storytelling through StatsMonkey, a data-driven narrative generation system capable of automatically producing coherent sports reports from structured datasets. This work marked an important step toward automated narrative generation and highlighted the potential of AI-driven storytelling in real-world communication contexts.

Mani (2013) further argues that computational models of narrative provide systematic frameworks for representing story events, character actions, causal relationships, and temporal sequences. Such models enable artificial intelligence systems to analyse, interpret, and generate coherent narratives by simulating the structural and semantic aspects of storytelling. This approach has significantly contributed to advancements in computational narrative intelligence and automated story generation by facilitating more sophisticated forms of narrative understanding and production.

Advances in machine learning and large-scale language modelling have transformed narrative generation. Large textual corpora and multimodal datasets combining text, images, and visual information have significantly improved AI-generated narratives (Dodge *et al*., 2021; Radford *et al*., 2021). These developments have enabled AI systems to generate increasingly coherent and contextually rich stories, although challenges related to consistency, cultural awareness, and emotional depth remain. Halperin and Lukin (2023) further demonstrate the potential of multimodal narrative systems in visual storytelling environments.

Large-scale datasets have played a crucial role in advancing computational narrative research by providing structured resources for training and evaluating AI systems. Levi *et al*. (2020) introduced CompRes, a dataset specifically designed to capture narrative structures within news discourse. The dataset enables researchers to examine relationships among events, characters, causal sequences, and narrative progression, thereby facilitating the automated analysis and interpretation of complex narrative patterns. By providing large-scale annotated narrative data, CompRes contributes to the development of more sophisticated narrative intelligence systems capable of understanding story structures, identifying meaningful connections between events, and generating coherent narrative representations. Such datasets are essential for improving the contextual awareness and narrative comprehension capabilities of contemporary AI models.

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Gatys, Ecker, and Bethge (2015) demonstrated the transformative potential of deep neural networks for creative generation through their pioneering work on neural style transfer. Their research showed that artificial intelligence can generate novel creative outputs by combining content and stylistic features from different sources, thereby influencing subsequent developments in computational creativity and generative AI systems.

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Theoretical frameworks from cognitive linguistics have also influenced narrative AI. Fauconnier and Turner's theory of conceptual blending explains how individuals combine diverse mental spaces to generate novel meanings and creative ideas. This framework has become increasingly relevant in computational storytelling and creative narrative generation, where AI systems attempt to synthesise information from multiple conceptual domains (Fauconnier & Turner, 1998).

Another significant area of research concerns cultural grounding and diversity in narrative generation. Crowdsourced knowledge systems have enabled the collection of culturally diverse information and narrative conventions from broad populations (von Ahn, 2006; Pratt, 2017). Such approaches enhance the inclusivity and contextual relevance of AI-generated narratives by incorporating varied linguistic expressions, cultural values, and storytelling traditions. Vázquez (2021) further argues that storytelling remains fundamental to computational narrative intelligence because it provides a framework through which machines can model human experiences and social understanding.

From a literary perspective, Arathdar (2021) examines the implications of artificial intelligence for literature, narrativity, and composition, arguing that AI-generated texts challenge traditional concepts of authorship, creativity, and literary production. The study highlights how emerging technologies are reshaping the relationship between human imagination and machine-generated narratives, opening new directions for narrative studies and digital humanities research.

Recent scholarship has increasingly connected narrative intelligence with education, sustainability, and leadership development. Studies on artificial intelligence literacy emphasise the need for human-centred approaches that balance technological advancement with ethical awareness and critical thinking (Alamäki, 2024). Schlauch (2025) highlights the growing significance of narrative computational thinking in educational environments, emphasizing the role of storytelling as a powerful medium for developing cognitive, creative, and problem-solving abilities. Through learners' interactions with digital authoring tools, the study demonstrates how narrative construction fosters logical reasoning, computational thinking, and reflective learning. By integrating storytelling with digital technologies, students are encouraged to organize ideas, understand causal relationships, and communicate complex concepts effectively. The findings suggest that narrative-based learning approaches not only enhance digital literacy but also promote creativity, collaboration, and critical thinking, making them valuable for the development of human-centred educational practices in the age of artificial intelligence. Similarly, research on AI-driven sustainable development and educational leadership highlights the importance of integrating human values into intelligent systems (Avurakoghene & Oredein, 2023; Kulkov, 2024; Tanveer, 2025). These perspectives suggest that narrative intelligence can serve as a bridge between technological innovation and socially responsible leadership.

Similarly, Abulibdeh (2025), through a systematic and bibliometric review of Artificial Intelligence in Education (AIED), demonstrates the growing significance of AI-driven learning environments and the need for responsible integration of artificial intelligence within educational systems. The study underscores the importance of human-centred AI frameworks that support learning, creativity, and sustainable educational development.

Methodological research has also contributed to the field by providing frameworks for evaluating AI-generated narratives. Thematic analysis offers systematic procedures for interpreting qualitative feedback (Braun & Clarke, 2006), while inter-rater reliability measures such as Cohen's kappa ensure consistency among evaluators (Cohen, 1960). Mixed-methods approaches and methodological triangulation further strengthen research validity by integrating quantitative and qualitative forms of evidence (Creswell and Plano Clark; Denzin). Statistical methods, including t-tests and ANOVA, remain essential tools for assessing differences in narrative performance across models and experimental conditions (Field, 2018).

Overall, the literature reveals a dual trajectory. Humanistic scholarship emphasises narrative as a fundamental mechanism for meaning-making, identity formation, and cultural continuity, whereas computational research focuses on enabling machines to generate, interpret, and evaluate narratives effectively. Bridging these perspectives is essential for developing narrative intelligence systems that are culturally grounded, emotionally resonant, contextually aware, and capable of supporting sustainable educational and leadership practices in the age of artificial intelligence.

3. Computational Narrative Intelligence

Computational Narrative Intelligence (CNI) refers to the capacity of artificial intelligence systems to understand, generate, interpret, and respond to stories in ways that resemble human narrative cognition. Winston (2011) identifies narrative intelligence as a defining characteristic of human cognition, arguing that stories serve as fundamental mechanisms through which individuals organise knowledge, communicate experiences, and interpret the world (Winston, 2011). Building on this foundation, computational narrative intelligence seeks to endow machines with the ability not only to answer questions about narratives but also to create original stories that reflect human emotions, cultural values, and social contexts (Riedl, 2016; Vázquez, 2021).

One of the central challenges in computational narrative intelligence is narrative comprehension. Unlike factual question-answering systems, narrative understanding requires recognition of implicit causal, temporal, and motivational relationships among events.

To achieve this, AI systems must develop mechanisms for representing commonsense knowledge and story structures embedded in natural language narratives (Schank & Abelson, 1977; Davis & Marcus, 2015). Research in narrative discourse modelling and story comprehension further demonstrates the importance of structured narrative representations in enabling machines to interpret complex stories effectively.

Another major area of research is machine story generation, where AI systems produce fictional narratives such as folktales, interactive stories, television scripts, and creative literary texts. Computational storytelling approaches draw upon narrative structures, plot planning, and character development to generate coherent and engaging stories (Finlayson, 2011; Gervás, 2009; Riedl & Young, 2014). Such narratives are valuable not only for entertainment but also for educational applications, cultural preservation, and the communication of ethical and social values (Riedl & Harrison, 2016).

Beyond fictional storytelling, computational narrative intelligence supports the generation of plausible real-world narratives that require reasoning, imagination, and causal inference. These capabilities have practical applications in educational simulations, training environments, forensic analysis, and decision-support systems. Narrative-based AI can also enhance virtual agents such as intelligent tutors, digital assistants, and healthcare coaches by enabling them to establish rapport through contextualised storytelling and personalised interactions (Riedl, 2016; Kannan *et al*., 2025).

Narrative intelligence further contributes to affective and emotional computing. Effective stories evoke emotional responses such as suspense, curiosity, empathy, excitement, or reassurance. Research on computational suspense and narrative engagement demonstrates how AI systems can model audience expectations and emotional reactions to create more compelling narrative experiences (O'Neill & Riedl, 2014; Veale, 2014). Such capabilities are increasingly relevant in journalism, entertainment, education, and human-computer interaction.

A further contribution of computational narrative intelligence lies in the domain of Explainable Artificial Intelligence (XAI). Narratives provide intuitive frameworks for explaining decisions, actions, and outcomes in ways that align with human reasoning processes. By presenting explanations as coherent stories that describe what occurred, why decisions were made, and how alternative outcomes might have emerged, AI systems can improve transparency and interpretability. Narrative-based explanations, particularly counterfactual narratives, offer a human-centred approach to understanding complex computational processes (Riedl & Harrison, 2016).

The development of computational narrative intelligence emerged from attempts to model storytelling processes computationally. Early symbolic approaches drew upon Vladimir Propp's structural analysis of folktales and David Rumelhart's story-schema theory. Subsequent research expanded into computational storytelling, narrative discourse modelling, and creative text generation (Finlayson, 2011). Algorithmic approaches such as Narrative Maps have been proposed to represent and extract information narratives from large datasets, enabling the systematic analysis of complex storytelling structures and narrative relationships (Keith & Mitra, 2020). Gervás (2009) highlights the role of computational creativity in narrative generation, while Riedl (2016) identifies computational narrative intelligence as a central goal for creating human-centred AI systems capable of understanding and producing meaningful stories.

Algorithmic approaches such as Narrative Maps have been proposed to represent and extract information narratives from large datasets, enabling the systematic analysis of complex storytelling structures and narrative relationships (Keith & Mitra, 2020). Similarly, narrative sensemaking techniques employ narrative maps to organize events, actors, and relationships, facilitating a deeper understanding of narrative structures, information flow, and meaning construction within complex datasets (Norambuena *et al*., 2021).

Ultimately, computational narrative intelligence extends beyond technical problem-solving to the

broader goal of machine enculturation. Through narrative understanding and generation, AI systems can learn cultural norms, social values, and ethical frameworks embedded in human stories (Nahian *et al*., 2020; Riedl & Harrison, 2016). Consequently, computational narrative intelligence represents a transformative step toward developing AI systems that are culturally grounded, emotionally aware, socially responsive, and capable of meaningful interaction within human communities.

4. Theoretical Framework

This study adopts an interdisciplinary theoretical framework that integrates narrative theory, cognitive psychology, computational narrative intelligence, and digital storytelling studies. The framework draws upon Jerome Bruner's theory of narrative cognition, computational storytelling models, conceptual blending theory, posthuman perspectives, and narrative transportation theory to examine how both human-authored and AI-generated narratives construct meaning, coherence, and emotional engagement.

4.1 Bruner's Narrative Theory

Jerome Bruner, J. (1990) *Acts of meaning*. Harvard University Press, argues that human beings understand and interpret reality primarily through narrative cognition rather than through purely logical or scientific reasoning. Narratives serve as fundamental mechanisms through which individuals organise experiences, construct identities, and generate meaning Bruner, J. (1990). This perspective aligns with Fisher's Narrative Paradigm, which conceptualises humans as storytelling beings who make sense of the world through narratives Fisher, W. R. (1987).

Key principles of Bruner's narrative theory include:

- *Narrative as Knowledge*: Stories provide frameworks for interpreting actions, intentions, motivations, and social relationships Jerome Bruner, J. (1990).
- *Canonicality and Breach*: Narratives often emerge from disruptions of established norms and explore how these disruptions are resolved.
- *Perspective-Taking*: Every narrative reflects a particular viewpoint, emphasising the importance of interpretation and subjectivity in both human and AI-generated storytelling.

Bruner's theory is further supported by cognitive studies demonstrating that narrative structures facilitate memory, understanding, and commonsense reasoning (Schank & Abelson, 1977; Davis & Marcus, 2015). Consequently, narrative cognition provides an essential foundation for understanding both human storytelling and computational narrative intelligence.

4.2 Computational and AI Storytelling Models

Computational storytelling represents a major area of artificial intelligence research concerned with enabling machines to generate, interpret, and evaluate narratives (Riedl, 2016; Gervás, 2009). Early systems relied on symbolic narrative planning approaches, including:

- *Tale-Spin* (Meehan, J. R., 1976). *The metanovel: Writing stories by computer* (Artificial Intelligence Research Report No. 1. Yale University, Department of Computer Science). which generated stories using goal-directed character behaviour.
- Turner, S. R. (1993). *MINSTREL: A computer model of creativity and storytelling* (Technical Report No. GIT-CC-93/03). Georgia Institute of Technology, College of Computing. which employed case-based reasoning to produce creative narratives.

These systems attempted to model narrative structure through explicit rules and knowledge representations. Later developments expanded toward narrative discourse modelling and story comprehension frameworks (Elson, 2012; Finlayson, 2011; Chang *et al.*, 2014).

Contemporary storytelling systems increasingly utilise neural network architectures and Large Language Models (LLMs), such as GPT, which generate narratives by learning statistical patterns from extensive textual corpora (Dodge *et al.*, 2021; Radford *et al*., 2021). While these models exhibit remarkable fluency and creativity, they continue to face challenges related to narrative coherence, causal consistency, contextual grounding, and cultural sensitivity (Riedl; 2016 Halperin & Lukin, 2023).

Lieto (2021) advocates a cognitive design approach to artificial intelligence that integrates human cognitive processes such as reasoning, memory, learning, and problem-solving into intelligent systems. This perspective is particularly relevant to narrative intelligence because effective storytelling requires common-sense reasoning, contextual understanding, and the ability to interpret characters, emotions, and causal relationships. By incorporating cognitively inspired mechanisms, AI systems can move beyond statistical pattern recognition toward more human-centred forms of narrative generation and comprehension.

4.3 Conceptual Blending and Narrative Creativity

Creative storytelling often requires combining diverse ideas, experiences, and conceptual domains. Fauconnier and Turner's Conceptual Blending Theory explains how individuals integrate multiple mental spaces to generate novel meanings and imaginative narratives (Fauconnier & Turner, 1998; *The Way We Think*). This theory provides a valuable framework for understanding how both human authors and AI systems construct innovative storylines and generate creative narrative content.

Hobbs (1992) argues that metaphor and abductive reasoning are fundamental cognitive processes that enable individuals to interpret abstract concepts, infer implicit meanings, and construct coherent understandings of complex situations. Metaphors facilitate the transfer of meaning across conceptual domains, while abductive reasoning allows individuals to generate plausible explanations from incomplete information. These mechanisms play a vital role in human communication, creativity, and narrative construction, as they enable storytellers to convey nuanced emotions, symbolic representations, and culturally embedded meanings. In the context of computational narrative intelligence, Hobbs' insights highlight the challenges involved in developing AI systems capable of understanding figurative language, contextual inference, and creative expression. Incorporating such cognitive processes into artificial intelligence can contribute to the creation of more sophisticated narrative systems that generate culturally aware, contextually relevant, and emotionally resonant stories.

4.4 Digital Narrative and Posthuman Storytelling

Digital narrative scholarship has transformed traditional understandings of storytelling by emphasising interactivity, multimodality, and collaborative authorship. Aarseth's concept of ergodic literature highlights the active role of audiences in constructing narrative experiences, while Murray envisions digital environments as immersive narrative spaces that reshape storytelling practices (Aarseth, E. J. 1997).

From a posthuman perspective, technology increasingly functions not merely as a tool but as a participant in narrative creation. Hayles argues that digital technologies challenge conventional distinctions between human and machine authorship, thereby redefining concepts of agency, authenticity, and creativity (Hayles). Similarly, Dihal *et al.* (2020) demonstrate how cultural narratives surrounding intelligent machines shape societal perceptions of artificial intelligence (*AI Narratives*).

Digital storytelling scholarship highlights the convergence of artificial intelligence, interactive media, and computational creativity in the development of emerging narrative systems. Trichopoulos (2023) argues that contemporary storytelling environments increasingly integrate algorithmic processes, immersive technologies, and participatory narrative structures that reshape conventional storytelling practices. These innovations foster new possibilities for human–machine collaboration, enhance audience participation, and contribute to the creation of dynamic narrative experiences across diverse digital platforms.

Recent studies of digital storytelling further reveal the growing convergence of artificial intelligence, interactive media, and computational creativity in the development of emergent narrative systems. Trichopoulos (2023) observes that contemporary digital storytelling environments increasingly integrate algorithmic processes, immersive

technologies, and participatory narrative structures, thereby expanding the possibilities of narrative creation, audience engagement, and human–machine collaboration.

4.5 Narrative Transportation Theory

Narrative Transportation Theory, developed by Green and Brock (2000), explains how individuals become cognitively and emotionally immersed in stories. Transportation occurs when readers or audiences experience deep engagement with narrative worlds, resulting in increased emotional involvement and persuasive influence.

This theory provides an important framework for evaluating AI-generated narratives because it offers measurable criteria for assessing:

- Reader immersion.
- Emotional engagement.
- Narrative coherence.
- Audience identification with characters and events.

Studies on computational suspense and emotional storytelling further suggest that narrative engagement can be modelled computationally to enhance user experiences (O'Neill & Riedl, 2014; Veale, 2014).

4.6 Integrated Framework for Human-Centred Narrative Intelligence

By integrating Bruner's narrative psychology, computational narrative intelligence, conceptual blending theory, digital storytelling scholarship, posthuman perspectives, and narrative transportation theory, this framework provides a comprehensive basis for examining human-centred narrative intelligence in AI. It enables the analysis of narrative coherence, creativity, cultural grounding, emotional resonance, audience immersion, and ethical agency in both human-authored and AI-generated narratives. Furthermore, it supports the broader objective of developing AI systems that align technological innovation with human values, cultural understanding, and sustainable educational practices (Riedl & Harrison, 2016; Alamäki, 2024; Avurakoghene & Oredein, 2023).

5. Research Gap

Although AI has shown promise in education and sustainability, three key gaps persist. First, existing systems focus on efficiency but rarely integrate narrative-centred AI for leadership training. Second, the connection between explainable AI, narrative intelligence, and sustainability leadership remains underexplored. Third, there is a lack of empirical evidence on learners' perceptions of AI-driven narrative tools in leadership education. This study addresses these gaps by developing a conceptual and empirical framework that embeds human-centred narrative intelligence in AI-driven education, with a particular emphasis on sustainable manufacturing leadership.

6. Research Methodology

Methodology forms the foundation of any research study, providing a systematic framework that ensures credibility, reliability, and validity. Beyond procedural guidance, it serves as a philosophical and practical roadmap for addressing research problems, achieving objectives, and answering research questions with rigour.

This study investigates Human-Centred Narrative Intelligence in AI as a transformative approach to education and leadership training for sustainable manufacturing. Given its interdisciplinary nature, encompassing artificial intelligence, natural language processing, education, leadership development, and sustainability, the research requires a comprehensive and flexible methodological design. Accordingly, a mixed-methods approach is adopted.

Quantitative methods, including surveys and descriptive statistical analysis, will be used to identify measurable patterns and relationships in learner responses to AI-enabled training environments (Field, 2018). Complementing this, qualitative methods such as focus group discussions and narrative case studies will be employed to explore the nuanced, value-oriented dimensions of leadership development and learning experiences (Braun & Clarke, 2006).

The integration of quantitative and qualitative approaches through methodological triangulation enhances the validity and reliability of the findings while providing a holistic understanding of the research problem. Together, these methods reflect the central premise of the study that narrative intelligence in AI should remain human-centred to effectively foster sustainable leadership rather than functioning solely as a technical system.

6.1 Statement of the Problem

The rapid integration of artificial intelligence into education and industry has created significant opportunities for innovation while also presenting complex challenges. Although AI systems are increasingly employed for adaptive learning, personalised instruction, and decision support, they often prioritise efficiency and technical performance over human-centred values such as transparency, ethical responsibility, interpretability, and narrative understanding (Abulibdeh, 2025; Riedl, 2016).

In the context of sustainable manufacturing, effective leadership requires more than technical expertise; it demands reflective judgment, ethical reasoning, communication skills, and the capacity to articulate complex sustainability objectives (Avurakoghene & Oredein, 2023; Tanveer, 2025; Kulkov, 2024). However, existing leadership development programs seldom utilise the potential of narrative intelligence in AI to cultivate these competencies. As a result, AI systems frequently function as "black boxes," limiting user trust, engagement, and adoption (Pietsch, 2024; Alamäki, 2024).

This study addresses this gap by proposing and empirically evaluating a human-centred, narrative-driven framework for explainable AI in leadership education, with particular emphasis on sustainable manufacturing contexts (Riedl & Harrison, 2016; Riedl, 2016).

6.2 Objective of the Study

To examine how narrative intelligence, through AI-enabled tools, can enhance decision-making competencies and foster reflective, ethical, and transparent leadership practices in sustainable manufacturing.

6.3 Research Question

Can narrative intelligence enhance the decision-making abilities required for sustainable manufacturing leadership?

The study is guided by the hypothesis that AI-enabled narrative intelligence tools are perceived by learners as more effective in fostering reflective learning than traditional text-based systems. It further assumes that integrating explainable NLP models into leadership training enhances transparency and trust. Additionally, narrative intelligence in AI is expected to positively shape sustainability-oriented decision-making skills, while story-driven educational interventions are hypothesised to promote greater engagement and retention than purely data-driven instruction.

6.4 Conceptual Framework

The conceptual framework (Figure 3) integrates three dimensions:

i. *Narrative Intelligence (Human-Centred AI)*: Ability of AI to generate, explain, and contextualise learning through stories and case studies.
ii. *Educational Leadership Training*: Embedding storytelling and interpretability into manufacturing leadership curricula.
iii. *Sustainability Orientation*: Guiding leaders to balance technical efficiency with ethical, ecological, and social dimensions.

Flow of the Framework

Narrative Intelligence → Transparent AI Explanations → Reflective Learning → Improved Decision Intelligence → Sustainable Manufacturing Leadership

This framework positions narrative intelligence not just as a computational feature but as a pedagogical tool, aligning AI systems with human-centred values.

6.5 Research Design

This study employs a mixed-methods research design to examine the influence of computational narrative intelligence on the quality, coherence, and cultural

relevance of AI- generated narratives. Both quantitative and qualitative methods are integrated to provide a thorough evaluation aligned with the formulated hypotheses.

6.6 Model Development

Two categories of models will be developed for comparison:

Baseline Models: Standard language models without any narrative intelligence enhancements (Control group).

Enhanced Models: Models augmented with narrative intelligence frameworks, including:

Commonsense reasoning modules informed by knowledge-based and crowdsourced approaches to simulate human everyday reasoning (Roger Schank & Robert Abelson, 1977; Ernest Davis & Gary Marcus, 2015).

Multimodal training using corpora comprising text, images, and video to enrich descriptive and imaginative narrative generation (Jesse Dodge *et al*., 2021; Alec Radford *et al*., 2021).

Conceptual blending techniques derived from the theoretical framework proposed by Gilles Fauconnier and Mark Turner (2002), computationally adapted for creative narrative generation.

Crowdsourced cultural knowledge collected from diverse demographic communities to strengthen cultural grounding and narrative diversity (Luis von Ahn, 2006; Pratt, 2017).

6.7 Data Collection

The data corpus will be drawn from multiple sources to ensure narrative richness, diversity, and cultural representation. These sources include textual corpora comprising literature, folklore, and contemporary stories from diverse cultural contexts (Finlayson, 2011). In addition, multimodal datasets integrating textual narratives with images and relevant video content will be utilised to support more vivid and imaginative narrative generation (Dodge *et al*., 2021; Radford *et al*., 2021). Furthermore, crowdsourced cultural inputs, including region-specific idiomatic expressions, storytelling conventions, and cultural values, will be collected through surveys and ethnographic contributions to enhance cultural grounding and narrative diversity (von Ahn, 2006).

To illustrate the impact of culturally diverse data sources on narrative generation, Figure 1 presents a regional comparison of narrative performance across key dimensions, namely coherence, cultural relevance, and creativity. As shown in Figure 1, narrative outputs exhibit notable regional variations, reflecting the influence of cultural context on storytelling quality and imaginative expression. Regions with stronger cultural grounding demonstrate higher levels of creativity and cultural relevance, highlighting the importance of incorporating diverse cultural inputs into AI narrative systems.

6.8 Narrative Generation Procedures

Both baseline and enhanced AI models will generate narratives in response to structured prompts designed to assess different dimensions of narrative intelligence. The prompts will be grouped into three categories:

- Everyday real-life scenarios to evaluate logical coherence and causal reasoning.
- Culturally specific myths and traditions to assess cultural relevance and contextual grounding.
- Imaginative and metaphorical narratives to examine creativity, originality, and metaphorical depth.

As illustrated in Figure 2, the performance of AI-generated imaginative and metaphorical narratives varies across regions in terms of coherence, cultural relevance, and creativity. The results indicate that culturally grounded narrative frameworks contribute to more engaging, contextually relevant, and creative storytelling outcomes.

This design enables a balanced evaluation of logical consistency, cultural sensitivity, and creative expression, providing a comprehensive assessment of human-centred narrative intelligence in AI (Field, 2018).

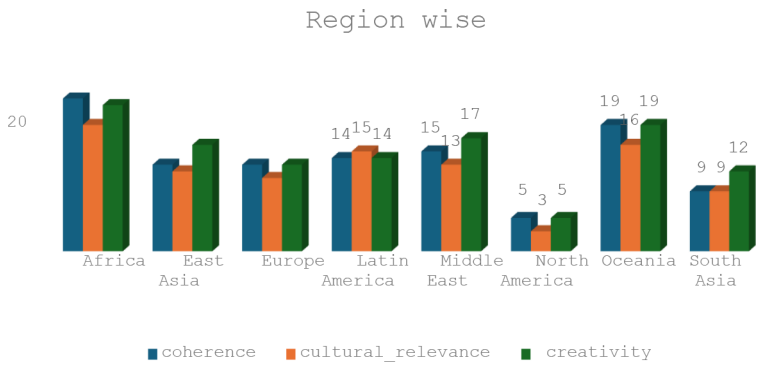


Figure 1. Regional comparison of coherence, cultural relevance, and creativity across different cultural contexts.

This design enables a balanced evaluation of logical consistency, cultural sensitivity, and creative expression, providing a comprehensive assessment of human-centred narrative intelligence in AI (Field, 2018).

6.9 Evaluation Framework

A hybrid evaluation strategy will be employed:

Quantitative Measures: Automated metrics including coherence indices (*e.g.*, causal or semantic continuity scores), lexical diversity, novelty/uniqueness scoring, and readability indices (pp. 41-44).

Qualitative Assessment: Blind human evaluators from diverse cultural backgrounds will rate the narratives using a Likert-scale rubric evaluating four dimensions: coherence, cultural relevance, creativity, and overall narrative quality (pp. 45-47).

6.10 Data Analysis

The generated narratives were evaluated across three key dimensions: cultural relevance, coherence, and creativity. The analysis examined performance variations among narratives based on cultural myths and traditions, everyday scenarios, and imaginative or metaphorical prompts.

As shown in Figure 3, narratives based on culturally specific myths and traditions achieved strong performance across all three evaluation dimensions, while imaginative and metaphorical narratives demonstrated the highest levels of cultural relevance and creativity. Everyday narratives exhibited comparatively lower scores, reflecting differences in narrative complexity and expressive depth.

Participant demographics were also analysed to understand the diversity of the evaluation sample. Figure 4 illustrates the distribution of participants according to their native language and age group. The demographic diversity of the participants contributed to a broader assessment of cultural relevance and narrative engagement.

Furthermore, participant perceptions of narrative quality and engagement were examined across different age groups. As presented in Figure 5, feedback varied among age categories, providing insights into how narrative intelligence and storytelling effectiveness are perceived by different demographic groups. These findings help evaluate the broader applicability and acceptance of AI-generated narratives across diverse audiences.

6.11 Evaluation Outcomes will be Analyzed Using Qualitative and Quantitative Methods

Statistical Tests: Paired-sample t-tests comparing baseline vs. enhanced models, and ANOVA when comparing across prompt types or model variations, to identify significant performance differences (pp. 48-50).

Thematic Analysis: Qualitative feedback will undergo thematic coding to surface patterns, strengths, and weaknesses perceived by human evaluators (pp. 51-53).

Inter-Rater Reliability: Cohen's kappa will be computed to gauge consistency across evaluator ratings (pp. 54-55).

6.12 Validation and Reliability

To ensure robustness, the study incorporates methodological triangulation, comparing automated metric outcomes with human evaluations to reinforce reliability and mitigate biases

Converging evidence across both evaluation layers strengthens the integrity of the findings (pp. 56-58).

7. Machine Learning Challenges

The development of automated story understanding and generation has long been central to artificial intelligence. Early approaches relied on formal, hand-crafted models of story worlds, which, while effective in narrow domains, were limited by the extensive knowledge engineering they required. With advances in machine learning, attention has shifted toward learning from large online narrative corpora and crowdsourced storytelling. However, this shift presents four key challenges.

i. *Human-centred Narration and Missing Commonalities*: Human stories are written for human audiences, drawing on shared knowledge often left unstated. For example, news articles emphasise unusual details while omitting routine elements. As a result, machines must infer implicit norms, a task complicated by data gaps. Crowdsourcing helps capture everyday narratives, but coverage remains incomplete.

ii. *Commonsense Reasoning*: Narrative intelligence requires commonsense knowledge, which humans acquire through lived experience. For machines, encoding this implicit knowledge, both declarative and procedural, remains difficult. Multimodal approaches that combine text with visual data (*e.g.*, images or videos showing everyday actions) offer richer avenues for capturing commonsense.

iii. *Figurative Language*: Stories often use metaphor, metonymy, and analogy, which demand deep semantic and cultural understanding. While computational methods have explored analogical reasoning and property mapping, figurative language still poses major obstacles for models dependent on surface-level statistical patterns.

iv. *Creativity and Beyond-pattern Learning*: True storytelling requires creativity, not just pattern repli-

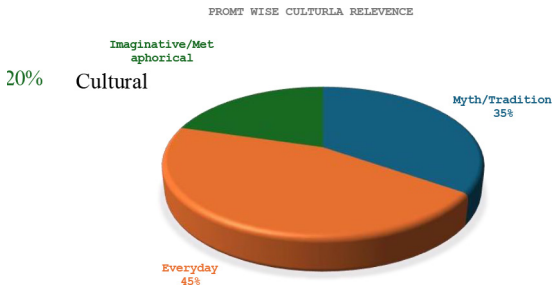


Figure 2. Imaginative and metaphorical narrative performance across regions.

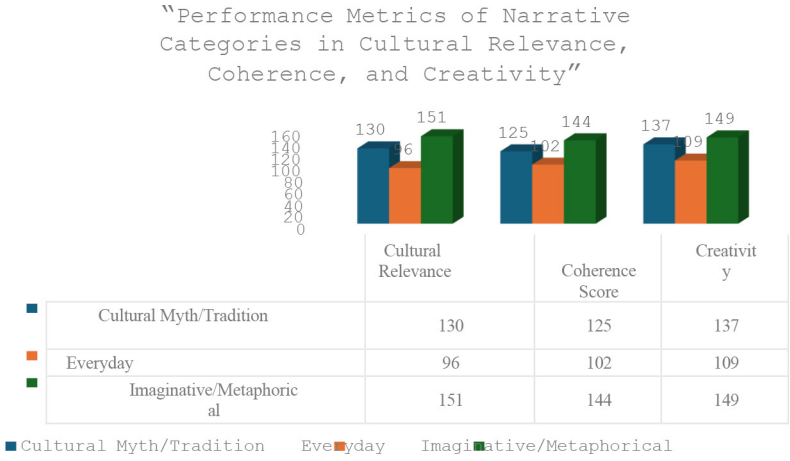


Figure 3. Performance metrics of narrative categories in cultural relevance, coherence, and creativity.

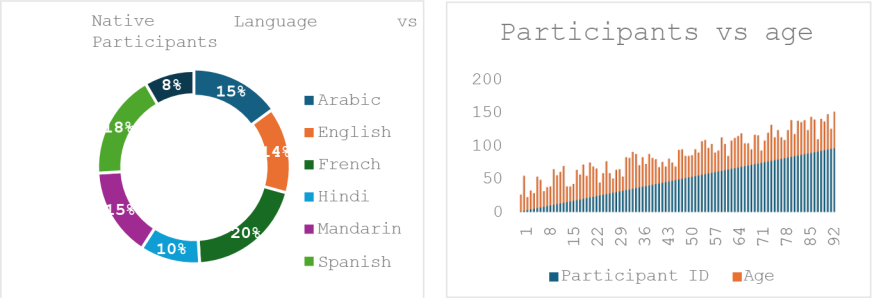


Figure 4. Distribution of participants by native language and age.

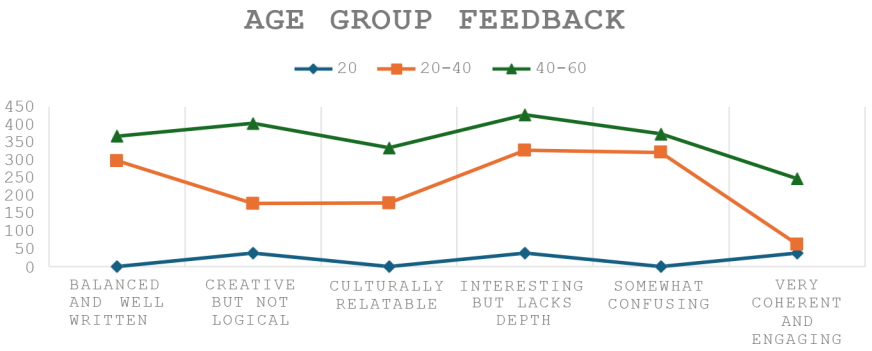


Figure 5. Age-group feedback on narrative quality and engagement.

cation. Statistical models often generate incoherent narratives because they struggle with long-term causal and thematic coherence. Techniques like LSTM networks and conceptual blending offer promise, but computational breakthroughs in creative story generation remain limited.

In sum, building open-domain narrative intelligence requires overcoming these four hurdles: unstated knowledge, commonsense integration, figurative language, and creativity likely through multimodal learning across text, images, and cultural artifacts.

8. Machine Enculturation

One of the promising directions in artificial intelligence is machine enculturation: the idea of teaching machines the social norms, values, customs, and etiquette that make human interactions meaningful and safe. Instead of programming every cultural rule directly, which is nearly impossible given the complexity of human society, researchers are exploring how AI can learn values through stories.

For centuries, humans have passed on moral lessons, shared ideals, and social expectations through narratives. From traditional fables that teach honesty and kindness to modern novels that wrestle with justice and identity, stories act as a mirror of culture. A tale like George Washington and the cherry tree, for example, conveys the virtue of truthfulness without ever spelling it out as a rule. Humans naturally infer these lessons, but for AI, capturing such implicit knowledge is far more challenging.

Characters in stories serve as role models: they make choices, face consequences, and embody values in context. If machines can learn from these examples, they could develop a deeper understanding of how to act in socially acceptable and ethically aligned ways. However, this is not without obstacles—stories often assume shared cultural background, use complex devices like flashbacks, or highlight events that are symbolic rather than directly actionable.

Still, narratives provide insights into mental states and social dynamics that machines cannot easily observe

in the real world. Approaches like Learning from Stories (LfS), demonstrated by Harrison, B., & Riedl, M. O. (2016) and Riedl, 2016 show that even simple, crowdsourced tales can help AI acquire cultural awareness. In this way, machine enculturation brings us closer to building AI that feels more human-aligned, trustworthy, and relatable.

9. Findings and Suggestions

The study revealed that different types of narratives offer unique strengths in shaping AI-driven storytelling for leadership and sustainability education. Folklore and traditional tales enrich narratives with moral, ethical, and symbolic depth, while contemporary stories provide relatable, real-world contexts that align with modern leadership dilemmas. Literary works add complexity and emotional resonance, helping AI generate narratives that blend intellectual insight with human-like reflection.

When multimodal sources such as text, images, and videos were integrated, learners found the narratives more engaging and immersive. Videos, in particular, encouraged situational learning by allowing learners to visualise leadership challenges in manufacturing settings. However, aligning imagery and symbolism across different cultures proved difficult, as interpretations varied widely.

Cultural insights gathered through crowdsourced idioms, metaphors, and storytelling traditions significantly increased relatability and authenticity. Learners connected more deeply with region-specific narratives, but the diversity of inputs also posed challenges for consistency across global audiences.

Based on these findings, several suggestions emerge. First, a balanced corpus that combines folklore, literature, and contemporary stories should be curated, avoiding over-reliance on any single source. Second, AI systems should be designed to harmonise multimodal data, ensuring that text, visuals, and sound enhance rather than conflict with each other. Third, dynamic crowdsourcing mechanisms such as storytelling platforms and surveys can keep narratives culturally grounded and up to date. Finally, cross-cultural validation is essential to ensure inclusivity. By localising idioms and embedding cultural values, AI-generated narratives can frame sustainability challenges in ways that resonate deeply, preparing leaders for ethical and sustainable decision-making.

10. Conclusion

Narrative intelligence plays a foundational role in nearly every aspect of human life. From the conversations we have daily to the stories we tell for entertainment, from the way we teach children to how we preserve history and values Modelling narratives are central to how we think, learn, and connect with one another. More than just a form of expression, storytelling serves as a vital mechanism for capturing and transmitting cultural knowledge, ethical principles, emotional understanding, and social norms across time and generations.

In this position paper, we propose that instilling computational narrative intelligence in artificial intelligence systems is not only desirable but necessary. By enabling machines to understand, interpret, and even generate narratives, we can bridge the gap between human and machine cognition. An AI equipped with narrative intelligence would be better suited to understand the context behind human actions, the intentions driving behavior, and the subtleties of human communication, such as metaphor, implication, and emotional nuance.

Such AIs would not only be more capable of engaging with humans in meaningful, relatable ways but would also be better positioned to explain their own decisions and actions in ways that humans can intuitively grasp. This interpretability is critical for building trust, transparency, and cooperation between humans and intelligent systems.

Furthermore, we argue that computational narrative intelligence provides a practical and scalable path toward machine enculturation the process of embedding social, cultural, and ethical understanding into artificial agents. Through exposure to diverse narratives, AI systems can learn patterns of behavior

that are considered appropriate, respectful, and safe within different cultural contexts. This, in turn, can help ensure that AI operates in ways that align with human values and avoids actions that might cause harm or social disruption.

Ultimately, developing narrative-aware AI is a key step toward creating socially intelligent, culturally adaptive, and ethically sensitive machine systems that are not only intelligent but also meaningfully human-compatible.

11. Future Scope

This study lays the groundwork for applying human-centred narrative intelligence in AI-driven education for sustainable manufacturing leadership. Future research can expand narrative corpora to include multilingual and cross-cultural stories, fostering inclusivity and intercultural competence. Immersive technologies such as AR, VR, and mixed reality can enhance multimodal learning, allowing leaders to experience complex sustainability challenges in realistic scenarios.

Longitudinal studies are needed to assess the lasting impact of narrative AI on leadership behaviour, ethical decision-making, and sustainability outcomes. Human-AI collaborative learning models can blend AI's adaptability with human instructors' creativity, creating interactive and adaptive pedagogical ecosystems. Industry-specific adaptations can extend applications beyond manufacturing, while ethical frameworks must address bias, cultural sensitivity, and learner influence. Pilot programs in educational and corporate settings can refine methods and evaluate scalability. Overall, narrative intelligence in AI offers immersive, insightful, and sustainable approaches to leadership training across diverse global contexts.

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Author Contribution

C. R. Usha was solely responsible for the conceptualization and development of the research study. The author conducted an extensive review of relevant literature related to artificial intelligence, narrative intelligence, digital humanities, and computational storytelling. The methodology, research framework, and model design were independently formulated and structured by the author. Data collection, analysis, interpretation, and comparative evaluation of narrative models were carried out exclusively by the author. The manuscript drafting, editing, proofreading, visualization of figures, and incorporation of reviewer suggestions were also completed by the author. The author has read and approved the final version of the manuscript and accepts full responsibility for the content and originality of the work.