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A New Approach to Information Hierarchy Based on Data Spaces and Intelligent Digital Twins: Cyclic Layers Model (CLM)

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Abstract

The rapid evolution of the digital era exposes the limitations of traditional hierarchical information models, such as Ackoff's DIKUW and Bellinger's DIKW pyramid, which fail to fully address contemporary challenges in data management and ethical technology use. This study introduces the Cyclic Layers Model (CLM) as a unified, holistic alternative that consolidates fragmented knowledge management approaches into a single, dynamic framework. Drawing from bibliometric analysis of 1074 publications (1985–2025) across major databases, and narrowing to 535 relevant studies, the model restructures information flow through cyclic, interconnected layers that incorporate individual, organizational, and environmental factors. By integrating Data Spaces and Intelligent Digital Twins (IDTs), the model offers a comprehensive approach to addressing ethical AI deployment, data privacy, and sustainability issues. This framework not only advances theoretical under-standing in knowledge management but also provides practical pathways for responsible decision-making in sectors such as healthcare and smart cities. CLM thus sets the stage for future multidisciplinary research aimed at designing ethically and culturally aware intelligent systems.

Keywords: DIKW pyramid, DIKUW, Data Spaces, Intelligent Digital Twins, Cyclic Layers Model.

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1. Introduction

Knowledge has long been regarded as one of the most valuable resources in both individual and organizational contexts. As Davenport [16] emphasize, knowledge is not a static repository of facts but a fluid mix of experience, contextual information, values, and expert insights that guide action. Unlike raw data or information, knowledge requires interpretation and contextualization, existing both at the individual level in cognitive skills, routines, and intuitions and at the collective level, where it becomes institutionalized through organizational norms and systems [35]. The big data era, marked by yottabytes of information, introduces unprecedented complexity in human-technology-environment interactions [30, 46]. Traditional models of information hierarchy, such as the classical DIKW (Data, Information, Knowledge, Wisdom) pyramid, assume a linear and stepwise transformation of data into wisdom. However, human cognition operates in a parallel and integrative manner, processing multiple streams of information simultaneously rather than sequentially [7, 18, 21, 42].

Originally formalized by Ackoff [2] to describe the transformation of raw data in-to wisdom through five categories -data, information, knowledge, understanding, and wisdom- the DIKW hierarchy gained traction through later adaptations such as Bellinger et al.'s [8] pyramid, which reframed "understanding" not as a distinct layer but as a supporting element [11]. Yet, Frické [19] and others highlighted a fundamental flaw in this hierarchy: the assumption that data can be linearly transformed into wisdom through inductive reasoning, often producing invalid conclusions. Frické [19] further criticized the model's reliance on operationalism and inductivism, which foster theory-less data collection and fail to account for the complexity, ethics, and context-dependence of modern knowledge systems. Complementing these critiques, Andreasik [3] demonstrates that knowledge management frameworks remain fragmented, falling into resource-based, process-oriented, knowledge-creation, or semantic categories. While each type contributes valuable insights, none offers a unified framework capable of holistically integrating technological, cognitive, ethical, and environmental dimensions. This fragmentation underscores the need for a comprehensive approach that transcends linear hierarchies and segmented models.

In response, the present study introduces the Cyclic Layers Model (CLM), a dynamic, spiral-based framework designed to replace rigid hierarchies with concentric, interactive layers representing data, information, knowledge, understanding and wisdom. Unlike static models, CLM emphasizes bidirectionality, contextual understanding, and the integration of ethical, cultural, and ecological principles into decision-making. Furthermore, it aligns with contemporary advancements in artificial intelligence, intelligent digital twin technologies, and data spaces, while promoting sustainability through principles of green computing and responsible AI. By unifying technological, ethical, and contextual considerations, the CLM provides a robust foundation for modern knowledge management applicable to complex domains such as healthcare, smart cities, and organizational decision-making.

2. Problem Statement

Despite the widespread adoption of the DIKW hierarchy and numerous knowledge management models, current approaches remain insufficient for addressing the realities of the digital era. Linear hierarchies fail to capture the integrative and context dependent nature of cognition while fragmented frameworks overlook ethical, cultural, and ecological dimensions of knowledge creation. At the same time, the exponential growth of digital data and the increasing reliance on artificial intelligence and digital twins demand models that can accommodate dynamic interactions among humans, technologies, and environments. These shortcomings create critical challenges in domains such as healthcare, smart cities and organizational management, where effective decision making requires the integration of cognitive, ethical, and technological dimensions. Therefore, there is a pressing need for a comprehensive, ethically grounded and multidimensional model that transcends linear hierarchies, unifies fragmented approaches and enables situated, sustainable and responsible knowledge use.

3. Literature Review

The DIKW hierarchy, often conceptualized as a linear progression from data to information, knowledge, and wisdom, has long served as a foundational framework in knowledge management, decision support, and organizational learning [2, 40, 54]. Data are viewed as raw facts, information emerges when meaning is ascribed, knowledge reflects the application of information and wisdom represents the ethical and contextual use of knowledge in decision-making. Despite its influence, critiques of the DIKW pyramid intensified following Frické's [19] seminal work, which highlighted logical inconsistencies, reliance on outdated operationalist philosophy and limited capacity to address the dynamic challenges of the Big Data and AI era. The COVID-19 pandemic further amplified scholarly attention, underscoring the model's inability to capture the complexity of technology-driven and ethically nuanced environments [3]. A bibliometric analysis of 535 studies conducted in this research confirmed a consensus among scholars that the DIKW hierarchy's linear structure neglects nonlinear cognitive processes, tacit knowledge and cultural contexts, prompting the development of alternative frameworks [19, 37, 44].

To overcome the limitations of the DIKW hierarchy, scholars have proposed alternative models integrating modern technological, ethical and interdisciplinary perspectives. Pop et al. [38] introduced the DIMLAK model, emphasizing semantic accuracy and interdisciplinary learning to define knowledge as a dynamic, ethical process. Acar et al. [1] proposed the EIK hierarchy to address educational challenges [5], while Kovalenko [29] developed the I-SDKW model for crisis management, processing heterogeneous data [5]. Ridi [39] suggested the DIKAS pyramid, redefining wisdom as awareness and Van Meter [48] introduced a Venn diagram approach to highlight flawed data risks. Yao [52] proposed the PCA model for intelligent systems and Sun et al. [47] developed the OPOP model to foster creativity in design education. Hautala [24] explored robots' tacit knowledge capacity and the need for transparency in human-robot collaboration, while Stavros [46] introduced the WKID Innovation framework, defining wisdom as "applied understanding." Zou et al. [55] proposed the DIKCW model with a focus on creativity and Grieves [20] redefined DIKW for Digital Twins. Wu & Duan [51] suggested the DIKWP-TRIZ model, emphasizing ethical innovation and Peters et al. [37] advocated for human-AI synergy, prioritizing human wisdom rooted in empathy and ethics.

Table 1 summarizes selected recent contributions to the DIKW framework, outlining their critiques and proposed extensions, though it represents only a subset of the broader literature. These efforts highlight the need for a comprehensive model addressing the epistemological, technological and ethical challenges of the Big Data and AI era. CLM provides such an integrative approach, incorporating Sustainable Knowledge Management to unify these dimensions effectively.

Author(s)	**Proposed Model**	**Criticisms of DIKW**	**Main Contributions**
Pop, I. G., et al. (2015)	DIMLAK (Data, Information, Messages, Learning, Advanced Knowledge)	Unclear boundaries	Ethical, dynamic knowledge
Acar, W., et al. (2015)	EIK (Environment, Information, Knowledge)	Misaligned with modern needs	Education-focused framework
Kovalenko, O. (2018)	I – SDKW (Intelligent Situational Data, Knowledge, and Wisdom)	Inadequate for heterogeneous data	Situational management support
Ridi, R. (2019)	DIKAS (Data, Information Processes, Information, Awareness, Self-Awareness)	Lacks wisdom clarity	Awareness-based wisdom
Van Meter, H.J. (2020)	Venn Diagram	Ignores incorrect data	Highlights data misuse risks
Yao, Y. (2020)	PCA (Perception, Cognition, Action)	Weak in complex systems	Tri-level thinking for analytics

Sun, Y., et al. (2021)	OPOP (One Product/Project/Performance, One Paper)	Logical flaws	Creativity in design education
Hautala, J. (2021)	DIKWP – AC (Data, Information, Knowledge, Wisdom, Purpose - Artificial Consciousness)	Ignores robot knowledge	Transparency in human-robot collaboration
Stavros, E. N. (2022)	WKID (Wisdom, Knowledge, Information, Data)	Cannot address Fails on wicked problems	Wisdom as applied understanding
Zou, L., et al. (2023)	DIKCW (Data, Information, Knowledge, Creativity, Wisdom	Lacks creativity	Creative intent analysis
Grieves, M. (2024)	Redefined DIKW	Definitional ambiguity	Fits Digital Twins, resource efficiency
Peters, M. A., et al. (2024)	Holistic Approaches	Neglects cultural dimensions	Human-AI synergy, ethical wisdom
Wu, K., & Duan, Y. (2024)	DIKWP-TRIZ	Ignores ethical issues	Value-driven innovation for AI

Table 1. Overview of Recent Studies on DIKW: Proposed Models, Criticisms and Contributions

Existing knowledge management models, while addressing DIKW hierarchy limitations like non-linearity, cultural sensitivity and ethics, remain fragmented, each tackling specific gaps (Table 1). Andreasik [3] classifies models into four groups, advocating for semantic and integrative frameworks to bridge theory and practice. Cristea & Căpățînă [15] review key models: Von Krogh et al. [49] emphasize knowledge in social interactions, Nonaka & Takeuchi [35]'s SECI model focuses on tacit-to-explicit knowledge transformation, Wiig [50] organizes knowledge into public, shared and personal forms, Boisot [10]'s I-Space model defines knowledge by codification and diffusion and Bennet & Bennet [9]'s ICAS model views organizations as adaptive systems. These models vary in addressing technological and ethical challenges. Spanellis et al. [45] propose iterative knowledge creation for innovative industries, while Karvalics [27] highlights classical models' inadequacy in VUCA environments, advocating technology-supported governance. These perspectives underscore the need for advanced, integrative frameworks.

4. Research Methodology

In this study, a comprehensive bibliometric review was initiated in March 2025 with a literature search, critically evaluating the limitations of the DIKW hierarchy. This review encompassed 1,074 publications retrieved from Web of Science, Scopus and PubMed using the keywords "data," "information," "knowledge," "wisdom," and "DIKW model." These publications are predominantly in English, with a few in Spanish and include peer-reviewed journal articles, conference papers and review articles.

	Web of Science	Scopus	PubMed
1985-2004	18	32	-
2005-2014	104	163	11
2015-2025	227	487	32
Total	349	682	43

Table 2. Distribution of Publications Across Databases (1985-2025)

Table 2 illustrates the distribution of publications across databases from 1985 to 2025, showing a marked rise in research output, especially post-2015, driven by Big Data, AI, and the COVID-19 pandemic's impact on knowledge management needs [25]. After removing duplicates and irrelevant studies, 535 articles were analyzed, segmented into three periods:

- 1985–2004 (foundational DIKW and traditional knowledge management),
- 2005–2014 (integration with digital and big data systems), and
- 2015–2025 (emergence of ethical, AI-driven, and sustainability-focused frameworks, including Data Spaces and Intelligent Digital Twins (IDTs)).

While IDTs and Data Spaces gained prominence post-2018, their roots in distributed systems, simulation and knowledge engineering trace back earlier, ensuring methodological consistency across historical and modern paradigms.

5. Research Results

Bibliometric analysis using VOSviewer reveals that since 2015, "DIKW" has become the most dominant concept, whereas earlier periods focused more on "knowledge management". Fig. 1 visually supports this shift, showing "DIKW" and "knowledge management" as central nodes with strong connections, indicating their prominence in the literature. These studies were evaluated in light of criticisms of the DIKW pyramid and proposals for its restructuring, as evidenced by the frequent co-occurrence of terms like "DIKW hierarchy" and "knowledge hierarchy" in the network [40, 54].

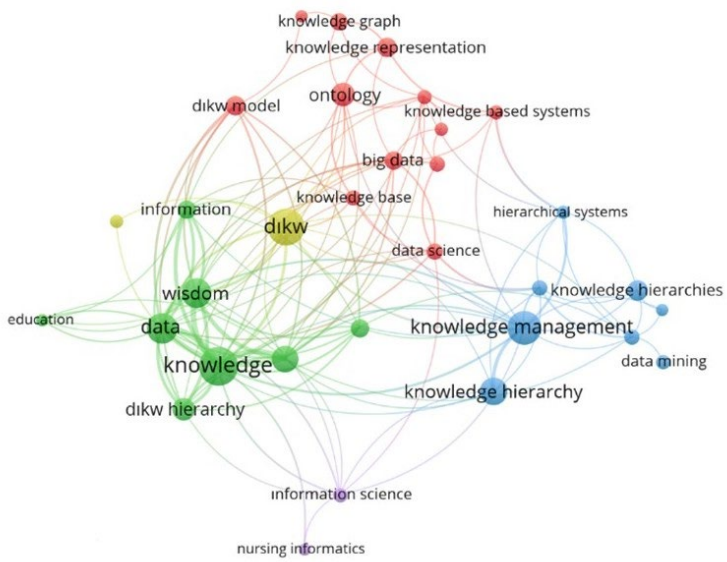

Figure 1. The Result of Bibliometric Analysis

The top publishing country is China with 128 publications, followed by the United States (90), the United Kingdom (36), Canada (23) and Australia (20). Gap analysis of the 535 studies indicates that the DIKW literature has entirely overlooked green computing and sustainability concepts, with ethics, data security, and cultural factors addressed only minimally. This gap is further confirmed by the absence of terms like "green computing," "sustainability" or "ethics" in the VOSviewer network map, despite the prominence of "big data" and "data science" post-2015. Although AI and IoT gained prominence after 2015, the "understanding" layer remains neglected, as evidenced by the lack of "understanding" as a node in the network map. CLM addresses these gaps by centering sustainability, green computing and cultural diversity, offering a framework that integrates these overlooked dimensions into the knowledge transformation process [36].

A thematic analysis of VOSviewer map clusters (green: knowledge, data, wisdom, education; red: big data, ontology) reveals DIKW's application in education and the neglect of ethical considerations in big data and ontology integration [54], while a time-series analysis post-2015 shows a shift from "knowledge management" to "DIKW," with the "understanding" layer often overlooked amid AI and IoT advancements [40]. A country-based comparison (e.g., China's 128 big data-focused studies vs. the UK's 36 education-focused studies) highlights cultural and technological influences on the lack of sustainability and ethics in DIKW research [1]. The absence of green computing in DIKW literature, as shown by VOSviewer, underscores the need to integrate Sustainable Knowledge Management and ethical frameworks into AI and IoT applications across DIKW layers [36]. Redefining the "understanding" layer as a bridge between knowledge and wisdom using AI-driven interpretive processes [54] further supports the development of the CLM, which addresses these gaps through a holistic, sustainable, and ethically grounded framework. This analysis not only strengthens the theoretical basis for CLM but also links identified gaps to the model's practical applications in subsequent sections, demonstrating how CLM's cyclic structure can be empirically tested in future studies through simulations or pilot implementations.

6. Proposed Model

6.1 The Framework of the CLM based on Data Spaces and Intelligent Digital Twins

The functionality of the CLM's layers is supported by a data space that integrates technologies like IoT, AI and IDTs to mirror the complexity of physical reality, defined as an intelligent digital twin of the existing space where data, information, and interactions converge, akin to the human brain's simultaneous processing of data and information [20, 51]. An IDT, as defined by Grieves [20], extends the traditional Digital Twin concept by incorporating AI and advanced analytics, enabling autonomous learning, analysis and decision-making. Unlike a standard Digital Twin that merely replicates a physical entity digitally, an IDT leverages realtime data integration and predictive analytics to optimize systems, make proactive decisions and collaborate with humans in ethical and contextual decision-making, crucial for the model's Understanding and Wisdom layers by providing contextual insights (e.g., assessing stress levels in healthcare) and supporting ethical decisions (e.g., evaluating treatment plans within cultural and ethical contexts) [20]. The spiral illustrates both inward (data-to-wisdom) and outward (wisdom-to-data) flows, emphasizing the model's bidirectionality (see Fig. 2).

This structure operationalizes the Data Layer as a repository for raw data while supporting transformation processes in the Information, Knowledge, Understanding and Wisdom layers. Zhang & Zhao [53] highlight that astronomical data, characterized by the four Vs -volume, variety, velocity, and value- requires advanced data management systems; the data space addresses these challenges by integrating heterogeneous data sources, aligning with the Virtual Observatory (VO) concept, a collection of interoperating data archives and software tools offering transparent, distributed access to global data [53]. The Cognitive Space, Concept Space and Semantic Space concepts by Wu & Duan [51] provide a systematic understanding of the data space's operations, aligning with Baskarada's [6] semiotically informed DIKW framework. Cognitive Space represents the transformation of data and information into understanding, Concept Space analyzes how individual (intelligence, character) and environmental (cultural context, geographical conditions) factors relate to data and information, and Semantic Space produces objective meaning, contributing to ethical, empathetic, and cultural contexts at the Wisdom layer [6, 34]. The Knowledge Galaxy represents the broader ecosystem of interconnected insights, while Data Spaces serve as its fundamental building blocks, enabling structured and context-aware integration of information (see Fig. 2).

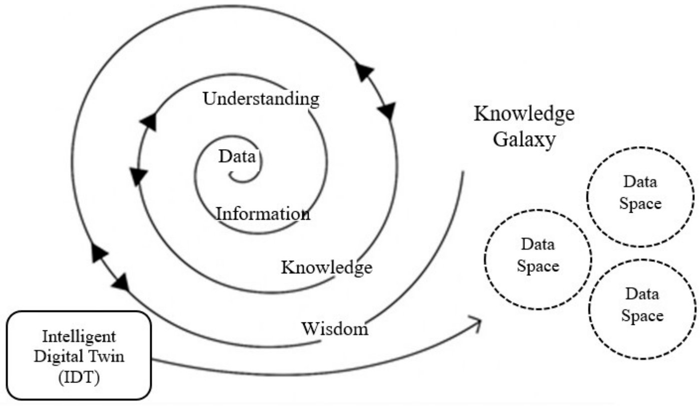

Figure 2. Cyclic Layers Model (CLM) based on IDT and Data Spaces

Supported by IDTs, this transformation enables the data space to function as a digital twin responsive to the digital age's needs; for instance, in healthcare, an IDT creates a digital patient representation, interprets symptoms in the Cognitive Space, relates them to medical concepts in the Concept Space and suggests an ethical, culturally appropriate treatment plan in the Semantic Space [20]. Zhang & Zhao [53] note that tools like AstroML and Weka address the "curse of dimensionality" in astronomical data, a challenge the data space tackles using AI to process complex datasets, balancing individuals, technology and the environment for meaningful, sustainable decisions. The data space should incorporate knowledge processing and decision-making systems that reduce environmental impact, with IDTs evolving into green digital twins through carbon-neutral data flows and sustainable systems, addressing the sustainability gap [31, 36, 53]. The CLM builds on their analysis by synthesizing the strengths of these models (e.g., SECI's cyclical knowledge transformation, Von Krogh et al. [49] connectionist perspective) while addressing their shortcomings through the integration of Data Spaces, IDTs and ethical frameworks. By positioning Understanding as a central layer and emphasizing bidirectional interactions, the CLM offers a dynamic alternative to the linear DIKW hierarchy, aligning with the call for non-linear, context-sensitive knowledge management frameworks. In the CLM, the "wisdom" layer is redefined not merely as the topmost layer but as a mechanism, marking a theoretical breaking point. Additionally, the "understanding" layer is positioned as an independent layer, methodologically addressing Frické's [19] critiques, rather than serving solely as a transitional stage between data, information, and knowledge. This approach is consistent with the one advocated by Grieves[20], and Table 3 compares the characteristics of Ackoff DIKUW, Bellinger DIKW, and CLM.

	Ackoff DIKUW	Bellinger DIKW	CLM
Layers	D-I-K-U-W	D-I-K-W	D-I-K-U-W (cyclical)
Structure	Hierarchical, linear	Pyramid, linear	Spiral, bidirectional
Ethics/ Sustainability	Ethics present, no ecology	Absent	Ecological ethics, green computing
Innovation	Focus on know-how	Pattern recognition	IDT/AI integration, cultural lens

Table 3. Knowledge Model Characteristics

6.2. Layers of CLM

The model's five cyclic layers were selected through a systematic synthesis of critiques [19], bibliometric findings and alternative models (Table 1), adopting a cyclical structure to reflect the brain's nonlinear processing [18, 42]. The layer names retain Ackoff's [2] terminology for continuity but are redefined to address Frické's [19] critique of DIKW's narrow definitions and to integrate individual differences (e.g., intelligence, character), environmental factors (e.g., cultural context), and technologies (e.g., IoT, AI, IDTs), as supported by [20, 51, 53]. The reintegration of the "Understanding" layer, omitted by [8], responds to Ackoff's [2] original inclusion and Frické's [19] emphasis on propositional knowledge. The spiral structure represents not only a flow from data to wisdom, but also a return from wisdom to data and bidirectional interactions decoupled between layers (see Fig. 2).

The Data Layer gathers raw signals from human senses (including interoception [12, 14, 33]) and IoT devices (e.g., soil moisture sensors [25, 28]), defined as "physical signs" [6, 54], handling large-scale astronomical data challenges [53]. **The Information Layer** transforms data into meaningful insights via AI, such as irrigation needs [51], using low-carbon servers for sustainable processing [36, 40]. **The Knowledge Layer** integrates information into actionable insights, such as optimizing irrigation timing using intelligent digital twins (IDTs) [20], embedding Sustainable Knowledge Management through energy-efficient storage [31, 51], and incorporating propositional knowledge to address critiques [19, 54]. **The Understanding Layer**, reintegrated per Ackoff [2] and Frické [19], contextualizes knowledge through ethical, empathetic (via interoception [14]), and cultural lenses [37], using IDTs for insights like healthcare stress levels [20, 36]. **The Wisdom Layer** enables ethical, goal-oriented decisions through ecological and cultural filters [17, 37], leveraging IDTs for collaborative outcomes (e.g., ethical treatment plans [20, 53]) and aligning with phronesis [2, 6, 51] and sustainability goals [31], reducing data center energy footprints [36]. This human-centered, sustainable model supports interdisciplinary applications in AI, IoT and cyber-physical systems.

6.3. Application Scenarios for CLM

To illustrate the application of the layers of CLM in a real world context, Singapore's Smart Nation initiative is examined as an example. Table 4 illustrates how sustainable and adaptive urban governance can be achieved when Singapore's Smart Nation Initiative is organized according to layers of CLM and Smart Digital Twins (SDTs) [22,23,43].

CLM Layers	Smart City Applications
Data Layer	Continuous streams of raw signals are captured from IoT devices, environmental sensors, GPS trackers, public transport infrastructures and citizen-generated mobile applications. Examples include real-time records of traffic density, electricity consumption, air quality indices and water usage levels. At this stage, these signals remain isolated and lack intrinsic meaning.
Information Layer	Through semantic integration and visualization platforms, raw signals are contextualized to form meaningful insights. For instance, the system identifies which districts experience peak energy consumption, when traffic congestion intensifies, or where air pollution surpasses safe thresholds. This transformation marks the transition from discrete data points to structured, actionable information.
Knowledge Layer	Multimodal datasets are correlated to uncover systemic patterns. Machine learning–enabled IDTs analyze long-term energy demand curves, traffic flows and weather variables to establish predictive relationships. Insights such as "air-conditioning demand drives summer energy peaks" or "rainfall

	significantly affects morning commute delays" emerge, producing generalizable knowledge that informs policy design.
Understanding Layer	Knowledge is interpreted within broader socio-technical and cultural contexts. Here, tacit expertise of urban planners and policymakers is combined with IDT-driven simulations. For example, the system not only predicts congestion but also allows experts to explore "what-if" scenarios—such as whether offering tax incentives for green buildings could reduce carbon emissions by 10% or whether dynamic road pricing might decrease Friday evening congestion. This layer provides causal explanations and bridges technical analytics with human judgment.
Wisdom Layer	At the highest level, ethically filtered and purpose-driven decisions are enacted. IDTs simulate alternative futures under conditions such as heatwaves or population growth, ensuring that decisions are sustainable and equitable. Examples include dynamic synchronization of traffic lights to alleviate bottlenecks, adaptive energy pricing to balance grid loads, or the strategic placement of electric vehicle charging stations to accelerate the transition to low-carbon mobility. These decisions reflect not only technical optimization but also alignment with ecological, cultural and human-centered values.

Table 4. CLM Layers and Smart City Applications

Aligned with green computing principles, Singapore's Smart Nation architecture integrates edge computing, energy-efficient data centers and carbon-aware algorithms to minimize the environmental footprint of digital infrastructures. This ensures that the computational backbone of IDTs remains consistent with sustainability imperatives. In sum, the Singapore Smart Nation case demonstrates how the CLM-enabled spiral supports anticipatory governance, ethical decision-making and long-term resilience in urban systems. By continuously cycling from data to wisdom and back, the city evolves as a living, adaptive ecosystem - one in which human and machine intelligence coalesce to achieve sustainable futures.

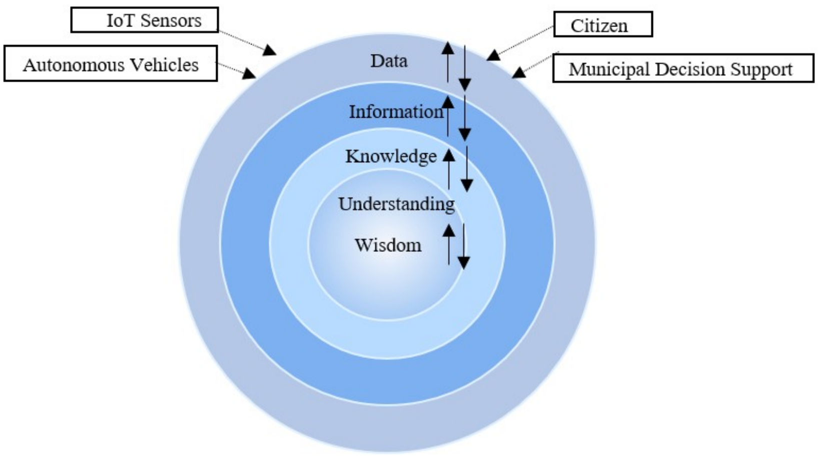

Figure 3. Cyclic Data-to-Wisdom Flow in Smart Cities with IDTs

Fig.3. illustrates the interaction between energy systems and autonomous vehicles within a smart city ecosystem. At the core, the cyclic layers represent the continuous flow of data, energy and intelligence across different domains. The spiral structures symbolize bidirectional processes, emphasizing the dynamic exchange of information between smart grids, renewable

energy sources and autonomous transportation networks. The diagram highlights how autonomous vehicles (self-driving cars, drones, and delivery robots) are interconnected with intelligent energy systems, ensuring efficiency, sustainability and resilience in urban environments. The cyclic and spiral architecture suggests a neural-synapse–like connectivity, reflecting the adaptive and evolving nature of smart city infrastructures.

In healthcare, Mayo Clinic demonstrates how the CLM cycle operates within patient-centered Intelligent Digital Twins (IDTs). Raw data from electronic health records, imaging, genomics, and wearables are transformed into information through structured dashboards and contextualized patient histories. Knowledge emerges when AI models integrate these multimodal streams to identify disease patterns or recommend personalized treatments. Understanding is achieved as physicians combine algorithmic outputs with clinical expertise, patient preferences, and ethical values. At the wisdom layer, IDTs simulate treatment outcomes -such as predicting that a certain cardiovascular therapy may increase long-term side effects- thereby guiding the adoption of safer alternatives. Crucially, when these decisions are applied in practice, new clinical results reenter the data space, creating novel datasets that reinforce subsequent learning cycles. This **wisdom-to-data feedback loop** exemplifies the bidirectional and cyclical essence of the CLM, while Mayo Clinic's adoption of green computing strategies (e.g., energy-efficient cloud platforms, federated learning) ensures sustainability in digital healthcare innovation [4, 32, 41]. This conceptual example underscores CLM's potential for real-world adaptation, with future empirical validation possible through simulated patient scenarios to evaluate decision accuracy and ethical compliance.

7. Conclusion

This paper introduces the CLM as a novel framework for information hierarchy, integrating Data Spaces and Intelligent Digital Twins (IDTs). Unlike the linear DIKW model, CLM employs a cyclic, bidirectional process, transforming data into wisdom and feeding wisdom back into data, thereby enhancing adaptability in socio-technical systems. Bibliometric analysis highlights underexplored areas in current research, notably the understanding layer and sustainability dimensions. CLM addresses these gaps by reinstating the understanding layer and embedding ethical, ecological, and sustainability principles. Application domains, including smart cities and healthcare, demonstrate CLM's potential. In smart cities, IDTs optimize energy and traffic systems, while in healthcare, they support ethical, patient-centered decisions, showcasing improved transparency and reduced risks. In addition, CLM incorporates principles of green computing (e.g., energy-efficient IoT design, carbon-aware scheduling) and cybersecurity (e.g., AI-driven anomaly detection, blockchain verification, and digital literacy), further strengthening its capacity to reduce environmental impact and safeguard human-data-system interactions.

The primary contribution of CLM is a holistic, multidimensional framework that overcomes the limitations of linear and fragmented approaches. However, as a theoretical model, it requires empirical validation through case studies, simulations, or real-world implementations. Future research will focus on operationalizing CLM by developing measurable indicators, testing its efficacy across diverse domains, and assessing its performance in real sociotechnical environments. In summary, CLM provides a robust foundation for sustainable, ethically responsible, and secure human-data-system interactions.

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