Triple Transition Ecosystem As Catalyst of Public Value Generation.

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Submitted: 31 January 2025, Revised: 26 March 2025, Accepted: 21 April 2025, Published: 22 May 2025

Abstract. Digital transformation is increasingly reshaping the public and private sectors by enhancing the efficiency and quality of services. With the integration of emerging technologies such as Artificial Intelligence (AI), blockchain, and Internet of Things (IoT), this transformation is becoming a key driver in achieving the United Nations Sustainable Development Goals (SDGs). This shift has given birth to concept of the "triple transition" emphasizes the interconnected the social, green and digital transitions as part of a systemic approach to achieve the SDGs. However, for these technologies to generate meaningful public value, they must rely on high-quality, accessible, and interoperable data. Public Data Ecosystems (PDEs) , as networks of stakeholders engaging in data exchange across the data lifecycle, provide a foundation for transparency and accountability as elements of public value. Their capacity to create broader societal and economic value remains limited without the synergy of advanced digital technologies. To this end, this study proposes the concept of Triple Transition Ecosystems (TTEs) networks of actors leveraging both PDEs and the four-intelligence (4I) paradigm (Data, Artificial, Collective, and Embodied Intelligence) to generate multidimensional public value aligned with the SDGs. Using a systematic literature review that includes thematic analysis informed by public value frameworks, we examine the potential of TTEs across various policy domains. Our findings indicate that TTEs have the potential to generate public value in terms of better service quality and governance, but also higher societal value. By conceptualizing TTEs, this study offers a novel framework for understanding digital transformation as a systemic enabler of sustainable development and provides actionable insights for researchers and policymakers seeking to design triple transition–oriented policies.

Keywords. digital ecosystem; public data ecosystem; public sector; SDG; triple transition; triple transition ecosystem
Research paper, DOI: https://doi.org/10.59490/dgo.2025.1008

1. Introduction

Digital transformation refers tothe adoption and integration of new technologies by stakeholders across both public and private sectors (Gong & Ribiere, 2021). This transformation is widely recognized for improving operational efficiency (Wujarso, 2023), as well as enhancing quality of services in diverse institutional settings (Dias et al., 2022). Fueled by the momentum of the Fourth Industrial Revolution, emerging technologies are now playing an increasingly pivotal role in reshaping organizational processes and governance models. In this context, the so-called four intelligence paradigm (4I) was introduced by Verhulst (2021) constituted by (1) Data Intelligence (DI) - technologies that process and analyze large datasets (e.g., IoT, blockchain) to inform decisions, (2) Artificial Intelligence (AI) - algorithms, including machine learning and expert models, that automate processes and enhance decision-making, (3) Collective Intelligence (CI) that refers to citizen participation via co-creation, crowdsourcing, or digital assemblies, empowering diverse input and democratized governance and (4) Embodied Intelligence (EI) that stands for physical devices and systems that interact with their environment, such as robotics and sensors, driving real-world applications of digital insights.The adoption of 4I technologies not only enhances operational efficiency and service quality but also offers transformative potential for advancing broader societal goals. These technologies contribute directly to the achievement of the Sustainable Development Goals (SDGs) by enabling more sustainable, inclusive, and responsive governance and service delivery.. E.g., AI can enhance energy efficiency by analyzing historical consumption data and identifying optimal patterns, such as aligning energy use with renewable energy surpluses (Farzaneh et al., 2021), blockchain can ensure secure and transparent data transactions, verifying the performance of public and private organizations in achieving SDG targets (Muheidat et al., 2022). Additionally, open data combined with citizen science initiatives amplifies diverse perspectives, fosters inclusivity, and supports informed decision-making to reduce inequalities and enhance societal outcomes (Moedas, 2018). The majority of the SDGs, such as those targeting climate action, poverty alleviation and gender equality are inherently linked to public value generation. This aligns closely with the emerging notion of the triple transition, the concept of the triple transition, which integrates digital, green, and social transformations into a unified framework for sustainable development. According to the OECD (2023), triple transition stands for "a systemic approach that places the interlinkages and interconnections of the environmental, digital, and social aspects of development at the core", while the EU (2023) refers to it as the social, green and digital transition, connecting it with the 17 SDGs. In this context, public value creation is multifaceted. Drawing on Meynhardt's (2009) framework, it can be understood across four dimensions, namely moral-ethical, hedonistic-aesthetical, political-societal and utilitarian-economic, each representing a critical aspect of how digital innovation can enhance collective well-being.

While all artifacts of the 4I paradigm have the potential of generating public value contributing to the achievement of the SDGs, their effectiveness is contingent upon the the availability of high-quality data. Accurate, complete, and reliable datasets are essential for trainingAI models that support informed decision-making, personalize user experience and improve service outcomes and customer satisfaction (Daneshjou et al., 2021; Deekshith, 2021).

In this context, Public Data Ecosystems (PDEs) emerge as foundational systems composed of data and diverse stakeholders ranging from public institutions and private sector to academia and citizens, interacting dynamically across the data lifecycle. PDEs facilitate the flexible exchange and management of data, enabling stakeholders to collaborate in data-driven decision-making. These ecosystems contribute to public value by promoting transparency and accountability through accessible information, such as fiscal records or environmental indicators, and by encouraging broad participation in data governance. While transparency and accountability align with moral-ethical and political-social values (Meynhardt, 2009), PDEs also have the potential to generate utilitarian and economic value – two types of values often disregarded by research. For instance, sustained growth in the data economy can drive innovation and long-term economic benefits, however, for such outcomes to be achieved, it is stipulated that PDEs are leveraged by emerging technologies (Farboodi & Veldkamp, 2022; Nikiforova et al., 2024), such as constituents of the 4I paradigm.

However, realizing this potential requires synergy between PDEs and 4I technologies. PDEs need technological enablers to unlock their full value, while 4I technologies rely on robust data ecosystems to function effectively.Addressing this interdependence by drawing upon the literature on PDEs, 4I and the triple transition (Pincheira et al., 2021; Farboodi & Veldkamp, 2022; Lnenicka et al., 2024; Nikiforova et al., 2024), we propose the concept of Triple Transition Ecosystem (TTE) that we define as a collaborative network of public and private actors, civil society, citizens and academia, in which stakeholders engage in data transactions and leverage 4I technologies to co-create public value and support the social, digital, and green transitions integral to achieving the SDGs. As TTE is built upon PDE, 4I, and triple transition, it is important to explore and conceptualize their convergence and potential for public value generation, which motivates this study.This study aims to conceptualize the TTE and explore its capacity to generate multidimensional public value by examining the convergence of PDEs and 4I artifacts. Specifically, we examine the roles of its key components - artifacts of the 4I paradigm and PDE. By investigating how these components contribute to public value creation, the study seeks to provide a deeper understanding of their interplay in fostering collaboration between public and private sector and civil society, driving innovation, and addressing societal challenges in the digital age. This research employs a systematic literature review (SLR), whose results are analyzed through thematic analysis, where to distinguish between types of public value being generated by TTE, a public value model inspired by the models of Meynhardt (2009) and Tweyzyimana & Andersson (2019) is used for code generation.

The results show that TTE has the potential to generate public value in a wide spectrum of policies, including land, tax, environmental, urban policy, as well as policies on cultural heritage, human rights, health and freight transport. Citizen participation, transparency, operational efficiency and sustainability are key elements of public value that can be generated by TTE. With this research we make a call for a discussion on the new concept of TTE and how public policy can promote their development in a manner that can spur the generation of public value.

The rest of the paper is organized as follows. In the second section, we provide a background on PDEs and the 4I paradigm, their potential to generate public value and their limitations and introduce the concept of TTE. The third section presents the methodology. In the fourth section, we present the results of the analysis with the fifth section constituting a discussion of the findings. The final section concludes the study.

2. Background

The process of digital transformation has become increasingly significant globally during the past decade, as both public and private services rely heavily on digital practices and processes (Alvarenga et al., 2020; Brunetti et al., 2020; Dener et al., 2021).

A parallel shift observed over the past decade is the global commitment of the United Nations (UN) members to the SDG agenda (Biermann et al., 2019). Countries worldwide are setting ambitious targets to address critical challenges, such as mitigating climate change, eradicating poverty and inequality, and fostering sustainable economic growth.

Digital technologies play a pivotal role in advancing SDGs (Mandejar et al., 2021), Jones et al., 2017). For instance, AI models can be trained on historical energy consumption data to identify consumption patterns that maximize energy efficiency. Examples include using energy when there is renewable energy surplus, recommending using appliances in the most efficient manner or finding the optimal time to use Vehicle to Grid (V2G) or Vehicle to Home (V2H) technologies (Farzaneh et al., 2021). Blockchain, in the form of a complex hashing algorithm, can be used for key and signature matching to verify data transactions, which can be helpful to avoid fraud during data exchanges that might be relevant to show the performance of public and private sector organizations with regards to achieving the aforementioned SDGs (Muheidat et al., 2022). Open data can also have an impact on SDGs. When effectively coupled with citizen science initiatives (as part of CI), it has the potential to amplify diverse perspectives and contribute to reducing inequalities by increasing transparency, inclusivity, and informed decision-making (Moedas, 2018), although yet to be improved.

Moreover, to monitor and evaluate the performance of public and private sector organizations against SDGs, coordinated data collection and analysis strategy, combined with robust digital governance frameworks (incl. data governance frameworks) are paramount. While data collection strategies focus on ensuring high-quality data collection in a cost-effective manner, while addressing concerns related to data privacy and anonymity concerns (Johnson & Turner, 2003), data governance frameworks encompass the entire data lifecycle—collection, storage, processing, and disposal (Abraham et al., 2019). This data collection is expected to be conducted in a manner that ensures the representativeness of samples from all affected groups, while also guaranteeing the quality and accessibility of data. Emerging technologies, such as IoT, drones, AI-driven tools and intelligent devices can enhance data collection from diverse sources (Plageras et al., 2018), thereby increasing representativeness of data and informing decision-making (Asghari et al., 2019; Plageras et al., 2018). Additionally, CI can significantly contribute to the data collection process. Initiatives such as living labs and crowdsourcing are effective in gathering data and public opinions on societal and environmental topics. These approaches not only enhance data diversity but also have the potential to democratize political decision-making (Hossain & Kauranen, 2015)—provided there are effective communication channels between citizens (that will participate in these collective initiatives) and decision-makers, and these channels are used actively and effectively (Hossain & Kauranen, 2015; Lnenicka et al., 2024).

PDEs, facilitating dynamic data exchange among diverse stakeholders (e.g., government, private sector, citizens, academia), possess the potential to significantly enhance data availability and contribute to the achievement of the SDGs by generating substantial public value.

PDEs can enhance transparency and accountability by increasing data accessibility for all stakeholders. Citizens, for instance, can readily access publicly generated data, such as fiscal, demographic, and socio-environmental indicators (e.g., unemployment, poverty, equality, environmental pollution), empowering them to engage more effectively in SDG-related initiatives. Moreover, increased transparency in data transactions fosters accountability by clearly delineating the contributions of each stakeholder within the ecosystem, ensuring data quality and completeness from all participating entities.

However, the concept of public value extends beyond trust and institutional legitimacy associated with accountability and transparency. Following Meynhardt (2009), public value encompasses the multifaceted relationships between individuals and the broader "society," encompassing all entities with which an individual interacts, including both public and private sector actors. Meynhardt (2009) categorizes these relationships as: (1) moral-ethical, (2) hedonistic-aesthetical, (3) political-social, and (4) utilitarian-instrumental. While accountability and transparency primarily align with moral-ethical and political-social values, a notable gap exists in the current discourse regarding the contribution of PDEs to other facets of public value, particularly the utilitarian-instrumental domain. This gap is exemplified by the limited exploration of strategies for operationalizing the data economy (Hilbert, 2016).

Regarding the utilitarian and economic value of data, it has been argued that a thriving data economy necessitates the conceptualization of data as a long-lived, depreciating, and tradable asset. To sustain long-term data value -and possibly it growth- it is imperative to integrate data into research and development activities, enabling continuous innovation and the accumulation of new knowledge (Farboodi & Veldkamp, 2022). Consequently, the effective utilization of data through emerging technologies to foster novel innovations can significantly enhance the societal value of PDEs. To this end, a new so-called four intelligence paradigm (4I) encompassing AI, DI, CI and EI (Verhulst, 2021)) seems reasonable to be addressed and integrated into the current landscape.

According to 4I (Verhulst, 2021), DI encompasses technologies and methodologies that enable the analysis and processing of large datasets generated from diverse sources, including devices, sensors, and operations within both public and private sectors. The processing and analysis of such data within the DI framework hold significant potential for enhancing decision-making processes. Three key components constitute DI:

1. **open data** that refers to data systems, where all stakeholders within a data ecosystem have consistent access to datasets, enabling them to analyze, utilize, and redistribute databased on their specific interests and motivations;

2. **data collaboratives** resembling living labs and citizen science projects that are typically led by private sector entities in collaboration with civil society, through which data is exchanged to generate public value;

3. **IoT** that facilitate the real-time extraction and availability of data generated by devices, with common applications including household electronic appliances and sensors strategically placed within infrastructure grids, such as water or energy systems;

4. **Distributed Ledger Technologies (DLT)/blockchain** technologies that contribute to DI by employing advanced cryptographic techniques to ensure data storage and distribution in a transparent manner, while addressing privacy concerns through mechanisms like "smart contracts."

Artificial Intelligence

AI within 4I is defined as computational processes designed to perform tasks traditionally carried out by humans (Verhulst, 2021). AI has evolved to include models capable of informing decision-making processes. Two primary artifacts of AI relevant to the intelligence paradigm are:

1. **Machine Learning (ML)** that leverage data to "learn" and generate actionable insights, thus informing decision-making processes;

2. **expert models** specifically designed to replicate human cognitive processes, with their application restricted to decision-making tasks.

Collective Intelligence (CI)

CI, in turn, shares similarities with data collaboratives but focuses on engaging individuals, irrespective of their stakeholder group, to foster citizen participation (Verhulst et al., 2021). CI manifests in several forms, with individuals contributing via smart devices or participating in physical events, such as citizen assemblies, with key artifacts of:

1. **participatory co-creation** involving the use of technological tools to gather data from stakeholders across an ecosystem, which is particularly relevant to geospatial data, where mapping tools integrate individual contributions with spatial datasets;

2. **(smart) crowdsourcing** that, while similar to participatory co-creation, focuses on collecting qualitative data, such as community improvement ideas or problem identification, from stakeholders;

3. **(digital) citizen assemblies** that combine networking opportunities with digital tools in physical settings to enable citizens to co-create policies. Unlike crowdsourcing, citizen assemblies operate with a defined agenda centered on local policies, leading to the designation of these initiatives as "crowdlaw."

Embodied Intelligence (EI)

Finally, EI encompasses AI components that are used in the physical world (Verhulst et al., 2021). The main purposes include automation of industrial processes such as manufacturing, as well as providing real-world, and real-time information on matters such as air quality and health, with EI artifacts entailing:

1. **robots as** reprogrammable machines that can harness the power of AI software to perform automated tasks that have mostly been deployed in the manufacturing sector, with other applications being at a nascent stage;

2. **drones** (also known as unmanned aerial vehicles (UAVs)) - aerial vehicles that are either controlled by remote pilots or by AI software.

According to Verhulst et al. (2021), the interconnected paradigms of DI, AI, CI and EI with its unique artifacts and methodologies collectively enhance data-driven decision-making and citizen engagement. According to this intelligence paradigm, emerging technologies generate novel forms of intelligence that, either independently or in

combination, can enhance governance and drive innovation, contributing to addressing multiple SDGs.
However, the different types of intelligence have a similar gap ought to be addressed. They rely on high-quality, reusable data, which remains a critical gap. E.g., AI does not yield the expected results in sectors like healthcare because of the lack of adequate data availability with, radiology and nuclear medicine research and development entities requiring data to train AI models that can help more easily detect suspicious diseases based on X-ray scans (Kocak et al., 2019). However, there are no (public/open) data ecosystems yet developed that can help increase data availability, rendering the utility and potential for public value of AI in this sector rather limited. Similarly, DI artifacts require synergies with PDEs to increase their potential for public value generation. As an example, open data or data sharing initiatives in the horticulture industry can bring benefits to local farmers, who will have larger data availability that will help them make better investment decisions on their infrastructure (Cazacu et al., 2023). Data sharing can also help them make other types of decisions, such as switching crops (De Prieelle et al., 2020). Such examples are evidence for the need for data availability covering the different artifacts of the 4I paradigm that would facilitate generation of expected public value.

This, however, creates a certain controversy. On one hand, PDEs require synergies with artifacts of the 4I paradigm to generate forms of public value beyond transparency, accountability and openness. On the other hand, these technologies require data availability to have meaningful impact for the stakeholders that utilize them. To tackle this controversy, we introduce the concept of TTEs. We define a TTE as *an extensive network of actors, including public, private sector, civil society and citizens, which are actively involved in data transactions and by leveraging artifacts of the four intelligence paradigm facilitates maximization of public value, based on their own personal interests, primarily, but also for the public good*. This definition is informed by academic discourse about PDE and its subsets (such as ODE) and how they can operationalize the data economy (Lnenicka et al., 2024), as well as practical challenges associated with data availability for unlocking the application of artifacts of the 4I paradigm, such as AI (Daneshjou et al., 2021) and blockchain.

Whilst there has been research on the utilization of emerging technologies to generate different elements of public value (Madan & Ashok, 2023), such as increase efficiency of services or make operations more sustainable (Nishant et al., 2020), as well as the potential of PDEs to generate public value through transparency, openness and accountability (Reggi & Dawes, 2016; Lnenicka et al., 2022), there is lack of clarity on the holistic public value that their synergy -or what we refer to as TTEs- can create. Even though evidence from literature demonstrates that artifacts of the 4I paradigm require data availability to increase their impact, but also that PDEs alone have limited public value, there is a lack in studies examining the relationship between artifacts of the 4I paradigm and PDEs in the context of creating public value, which is the gap we address.

As such, the main objective of this study is to conceptualize a TTE comprising artifacts of the 4I paradigm and PDE, and explore its potential for supporting data-driven and evidence-based policymaking that results in public value generation. This will inform the exploration of the types of public value that TTE can create, in terms of societal, ethical, utilitarian and aesthetic value (Meynhard, 2006).

3. Methodology

To attain the set objective, a systematic literature review (SLR), followed by a thematic analysis to generate codes based on the potential of TTEs to generate public value is conducted. Code generation was informed by a meta-synthesis of the e-government public value framework introduced by Tweziyimana & Andersson (2019) and the public value framework by Meynhard (2006). Our SLR followed guidelines proposed by Kitchenham (2004), namely identification of research objectives, selection of primary studies, study quality assessment, data extraction and monitoring and data synthesis. The first step includes familiarization with the existing research, through preliminary research. As a second step, we identified keywords for the query, namely on the convergence between PDEs and artifacts of the four intelligence paradigm.The search query was defined as a combination of "public" and "data ecosystem" terms, where the latter was accompanied with alternative resulting in*("data ecosystem" OR "data infrastructure" OR "data space" OR "data system" OR "data collection ecosystem" OR "dataset* ecosystem" OR "data set* ecosystem" OR "data on the web ecosystem") AND ("public"),* which was used to query Scopus, WoS and Google Scholar.

The selection of the keywords with regards to PDE is justified by the multiple structures of data ecosystems that have been described or introduced by scholars (Lnenicka et al., 2024), which includes data infrastructure (Maretti et al., 2021), data ecosystem (Schade et al., 2015), data system (Formosa, 2014), as well as data space (McKenna, 2017). To make the connection to the 4I paradigm, the protocol was developed to document analysis of researched studies that examined the convergence of PDE with at least one of the 4I paradigm artifacts.

During the identification process, a total of 1,121 research papers were identified. After the screening process, 573 papers were excluded as sector-specific. Only studies pertaining to the fields of computer science, information technology, public administration, and engineering were retained as most relevant to TTEs, which are inherently linked to computer science, information technology, and engineering, with a public value component aligned with public administration and management. Only studies published in the period between 2014 and 2024 were retained to render the most relevant to this study, with older studies seen as less pertinent to TTE due to the rapid pace of technological advancements. Furthermore, the inclusion criteria encompassed conference proceedings, book reviews, and publications in scientific journals.

Subsequently, an eligibility analysis was conducted. During this stage, all studies in language other than English were excluded, reducing the pool to 370 studies. An eligibility check involved the manual exclusion of studies deemed irrelevant to the research topic based on title and abstract, as well as studies with only titles and abstract in English. As a result, only 152 research papers were selected for analysis (see Figure 1).

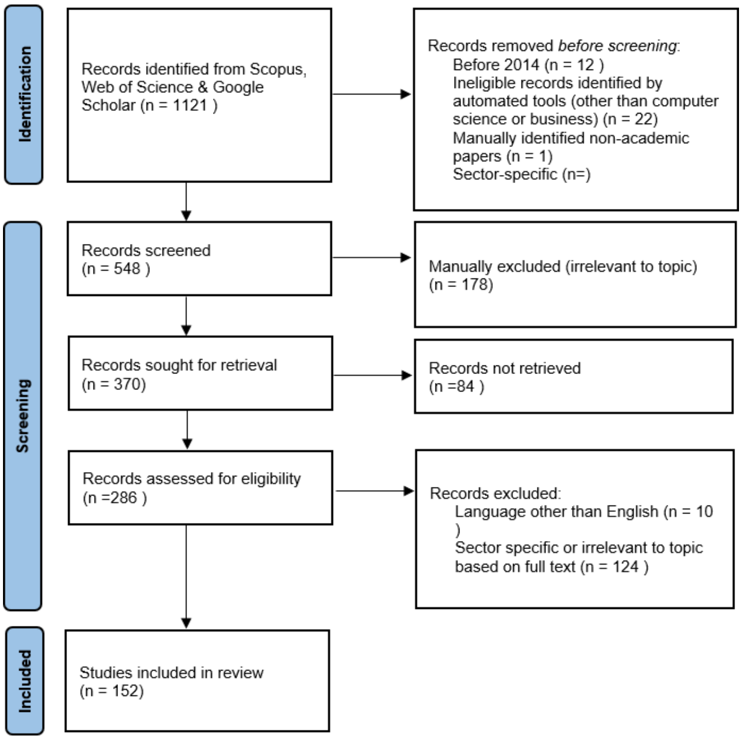

Fig. 1. Systematic Literature Review Process

The analysis of these studies was documented in a protocol developed by Lnenicka et al. (2024) to assess literature on PDEs. Following that, the final selection of studies was assessed based on this protocol that was developed as part of this research. The protocol consists of a series of questions that are presented in Table 1.

Tab. 1: Part of the protocol used in the SLR. The protocol will be disclosed in full in Zenodo upon paper acceptance.

Question Sector	Question
PDE-Specific	PDE/ODE Involved?
	Other terms related to ODE/PDE or other types of data ecosystems?
	If openness is not explicitly mentioned, does the study incorporate public and/or private components?
	- If yes, what is the structure of the ecosystem proposed?
	What stakeholders are involved in the ecosystem proposed?
	Which stakeholders are highlighted as most important?
	What types of data are involved in the ecosystem proposed?
4I-Specific	Is DI covered?
	Is AI covered?
	Is CI covered?
	Is EI covered?
	What are the artifacts it consists of/contains?
	Who are the stakeholders associated with the research on these types of intelligence and what roles do they fulfill?
	How is each type of intelligence affecting/what is its role in PDE/ODE?
	Is there any convergence of multiple intelligence paradigms?
	If so, what types of intelligence and what artifacts are involved?
	What artifacts are being integrated and through which methods/processes?

The next step included thematic analysis, which was conducted according to the six-step approach by Braun and Clarke (2006) extended by Maguire and Delahunt (2017). This approach suggests starting with familiarization with data, which is initiated after the SLR, followed by generation of the first set of codes that are then converted into themes. These themes are then reviewed and assigned final names and definitions, which we present in Results section.

Several public value frameworks informed development of the codes and themes. For example, the widely used public value scorecard proposed by Moore (2012) is used to assess the application of existing technological artifacts and systems and is not applicable for conceptual models, with the model by O'Flynn (2007) facing the same issues and targeting solely public managers. This comes in contrast with the theme of this study, which aims at conceptualizing the introduced term, encompassing stakeholders including private sector and citizens. Taking this into account, a meta-synthesis of frameworks took place. The initial framework that was used as a reference model for our integrated model is the model developed by Meynhardt (2006). Even though it is only conceptual framework, this framework can also be used for operational purposes and converted into a scorecard. As the framework is not directly related to assessing the public value of technology, the dimensions of public value are not broken down into the four categories provided by the author in his follow-up work (Meynhardt, 2009). Instead, the e-government public value framework, developed by Twizeyimana & Andersson (2019) is being adapted. According to this model, the dimensions of public value for e-government are improved public services, improved administration and improved societal value. The main categories of the e-government public value model are relevant for all digital technologies and all sectors (public and private), however the sub-categories are only relevant to the e-government sector. Hence, these categories are being reshaped and merged with the Meynhardt (2009) model into a framework as presented in Figure 2. All pillars from the model by Meynhardt (2009) were integrated into the category of the model by Twizeyimana & Andersson (2019) considering their individual suitability. For example, transparency and accountability fit most governance, whilst reliability and efficiency of services - improved service quality.

Fig. 2: Public Value Framework for TTE SLR

Based on this framework, the themes and codes that have been identified above as elements of public value are used to understand the type of public value that each instance of the TTE (PDE, four intelligence paradigm) can create. In addition, as part of the conducted SLR, we seek for identifying sectors/types of policy where the (potential) value of what we call TTE was studied.

4. Results

The results of our SLR show the convergence of PDEs and artifacts of the 4I paradigm as identified in literature can act as catalysts to generate public value in various policies. This convergence was found to have the potential to inform land, tax, environmental, urban, health, human rights, cultural heritage and freight transport policy, which we elaborate on in more detail below.

Land policy

TTEs in land registries hold promise to enhance operational efficiency in the public sector, even if the first attempts were not met with success. This is evidenced by Denmark in 2009, which was successful in reducing the time intensity of land registry procedures, but also faced deficiencies, such as the lack of mechanisms to verify land-related data, such as geographic data (Naghavi et al., 2022), which is suggested to be tackled by blockchain systems that harness PDEs. More specifically, Voluntary Geographic Information (VGI) systems constitute a new way of crowdsourcing of geospatial data (**CI** artifact), increasing **citizen involvement** (Naghavi et al., 2022). Combined with blockchain to verify and secure data transactions (**DI** artifact), they can be used by land registries and then visualized to improve **efficiency** and simplify the service itself (Kliment et al., 2016). This can be in a form of a private/restricted blockchain based on majority consensus, where the users can use hashing algorithms such as SHA256 or Proof-of-Work (PoW) algorithms to ensure the validity of geospatial data entered that are related to a piece of land, so that the land registry can update all the characteristics of different assets (Krishnapriya & Greeshna, 2020).

Tax policy/Compliance

The aforementioned use of blockchain (**DI**) and VGI (**CI**) systems extends to tax policy. Firstly, this combination can serve as a proof for the tax obligations that stem from land property. Secondly, other artifacts combinations with blockchain can support provision of tax obligations for other assets. As an example, images of assets (such as land property, houses) generated through citizens' devices can then be processed by **AI** for their categorization to understand the type of asset and their value (Petersen et al., 2019). The "cleaned" data can then be validated by blockchain, which can be converted into proof of assets for citizens, which can then be taxed accordingly, further improving **operational efficiency** for the departments of finance at local, regional and national governance level. Similarly, this can be used for whistleblowing cases, where illegal buildings or other assets are not registered and, through this digitized process and using citizen-generated data from PDEs changes in taxation or recompenses can be administered financially for **citizen participation** and **transparency** purposes. Finally, TTEs can increase efficiency, when Generative **AI** harnesses publicly available financial reports of firms and checks them against existing tax policies and regulatory frameworks (Chen et al., 2024).

Urban Planning

The transformative effect of TTE is also foreseen in urban planning. An example includes the proposition of PFLOW (Kashiyama et al., 2017), which proposes an open data system, where data inputs by citizens can be provided voluntarily about their movements, either within their vehicles, public transportation or on foot, to understand traffic patterns (**CI**). Such a system, complemented by a GIS system, has the potential to support urban planning through **citizen participation**. As the voluntary data generated and provided might require cleaning or verification, **AI** and blockchain (**DI**) can find their use in this context and, following that phase, the final datasets can be harnessed by urban planners to help making cities more livable, reducing traffic and improving **sustainability**.

Environmental policy

There is some evidence that environmental policy is a potential beneficiary of TTE. Environmental monitoring is one of the cases where TTEs can have added value. Open government data portals can enhance **transparency** of governments, increasing the availability of environmental data, such as CO2 emissions (Misra et al., 2017). However, this data should be provided in a clear format being easy to understand by diverse stakeholders, with every stakeholder having a suitable data literacy level (Hintz et al., 2023). For that to occur, **AI**'s data curation, cleaning, alignment, sketching and processing potential can make data clearer, understandable and reusable (Purawat et al., 2021), whilst data collaboratives (**CI**) can, in the long term, improve environmental data literacy among citizens (Verhulst et al., 2023). According to Shusha et al. (2023), developing an open data ecosystem (**DI**), where space data are deposited increasing **citizen participation**, has been largely beneficial for actors such as the Swedish Forestry Agency and other governmental entities that work on the environment in Sweden. While this research focuses on open data ecosystems, the concept can be expanded to a broader concept of PDEs OGD is a subset of, having the benefit of larger data availability due to the participation of more stakeholders in the ecosystem. Providing clean space data can support these agencies, as they can introduce them into their AI models (**AI** artifacts) and generate insights of expected environmental degradation under different environmental policy scenarios, thereby supporting **sustainability**. Other cases include smart cities, where sensors and IoT technologies (**DI**) are deployed within a city context referred to as "urban tech" and allow cars, buses, bicycles, and citizens to collect data about air quality, noise pollution, and the urban environment at large, through sensors installed in the vehicles, as well as devices operated by citizens (Zerza & Park, 2020). These types of data can be then leveraged by municipalities to understand the level of environmental degradation in real time, shaping policy accordingly and reducing the response time.

Another case where TTEs can be useful for environmental policy is energy and resource efficiency. Resource efficiency and overall environmental conservation requires even larger amounts of diverse data. E.g., while datasets with overall or even per region energy consumption can help inform policy making at a macro level, combination with geodata provides information on the energy consumption for individual buildings, which can result in a spatial visualization of energy consumption patterns and, thus, make interventions in buildings/neighborhoods where, for example, high energy usage is being observed. Other examples include using geodata to estimate the solar rooftop potential of each neighborhood and install photovoltaic panels where this potential is the highest (Mainzer et al., 2017). This, in turn, can take place using satellite imagery and drones (**EI**). Moreover, due to the large amounts of data processed by **AI**, there is the issue of sustainability that ought to be addressed, with green computing being one of emerging solutions to the sustainability conundrum, which includes e-waste minimization, as well as innovations such as energy efficient hardware, virtualization software and green algorithms, that result in the minimized use of energy during their runtime (Lannelongue et al., 2021).

Health Policy

Health policy can also largely benefit from a TTE. Ahmad et al. (2022) provide an overview of how healthcare can be transformed from this convergence in a smart city context. There are four models that can be used for digital transformation of healthcare. In healthcare 1.0, stakeholder participation in PDEs is very low, with no 4I artifacts and no public value associated with this model. In healthcare 2.0, there is slightly higher participation of stakeholders in PDEs, however, 4I artifacts are still not used and the only public value-related benefit is an increased efficiency. In healthcare 3.0, there is a high level of **citizen involvement** in PDEs, with EI artifacts such as wearables and artificially intelligent devices, resulting in **citizen participation** and **reliability** of results. Finally, in healthcare 4.0, there is a very high involvement of stakeholders and, in addition to **EI**, **DI** artifacts such as blockchain can be observed, as well as **CI** artifacts, such as citizen science (termed as big medical data) to ensure privacy, in addition to the foregoing public values.

Human Rights

A convergence of PDEs and artifacts of the four intelligence paradigm can be of use also for the human rights policy, in two manners. First, in relation to digital rights. Calzada & Almirall (2020) propose the development of GovTech labs in cities, using global examples and applying them to the case of Barcelona. These ecosystems employ public AI and public analytics, powered by blockchain (**DI**) to ensure anonymization processes and privacy-preserving procedures during co-creation in citizen science structures (**CI**), which include data commons. This is a dynamic type of infrastructure, whereby citizens actively provide their inputs in the data commons, which then are used to inform legislation around digital rights, leading to increased **citizen participation**. Human rights policy in general can be informed in a similar way. Nelson & Zanti (2020) propose a framework, where PDEs are complemented by data collaboratives (**CI**) and the use of machine learning tools (**AI**) to understand whether racial equality principles are respected in certain areas within a country. This is largely useful to inform policies relevant to minorities and indigenous communities in countries that have these populations, indirectly related to **human dignity**.

Cultural Heritage

In addition, policy around cultural heritage can be affected. E.g., Vahidnia (2023) explored how open data ecosystems can help inform urban decay through the support of VGI (**CI**), proposing a framework, where municipalities, civil society organizations and the private sector working on tourism develop a spatial data infrastructure (SDI), combined with a collection of other data, such as images, being crowdsourced by stakeholders and then introduced into a living lab (**CI**). These data are then processed within living labs and, following a co-creation process, policy recommendations are used to help preserve buildings of importance for **cultural heritage**.

Freight and Long-Distance Transport Policy

Lastly, the possibility of informing long-distance transport policy emerged as a pattern, with freight logistics in focus, in particular. Horizontal collaboration among stakeholders through smart contracts, using blockchain (**DI**), that harness open data and using **AI** to develop emission scenarios for different policies based on the aforementioned data is considered an efficient measure to track CO2 emissions in freight transportation from the governance side (Larsson et al, 2024). Environmental monitoring is deemed as the main reason for the utilization of this convergence in this case, resulting in enhanced **sustainability**.

Thus, TTEs have a role to play in several different policies as summarized in Figure 3.

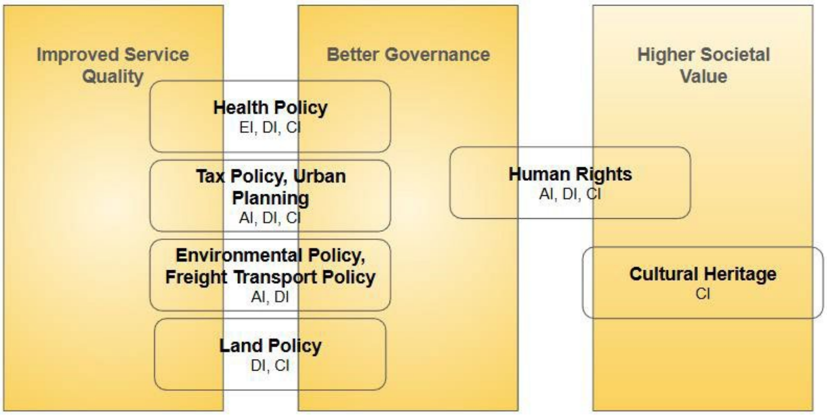

Fig. 3: Impact on TTEs in generating public value in policies

5. Discussion

The results show that TTEs hold promise to generate public value in various sectors and through several different means. Its approach can have benefits for policies in several sectors of the government. It can improve sustainability through energy efficiency in the built environment, which is a public value important in the smart cities sector. Local governments are increasingly implementing smart city initiatives and, according to the definition by the European Commission (n.d), upgrading energy and water infrastructure, as well as the built environment to become more efficient and sustainable is one of the key aspects of a smart city. Hence, TTEs have the potential to generate public value in the form of sustainability for the smart city realm.

Another sector where TTEs are a promising solution to generate public value is cultural heritage. This requires collaboration between macro and micro levels, namely national and local governments. The use of VGI and combination with AI can contribute to comprehending the level of decay that different cultural and historical heritage sites have undergone. Citizens' role can be instrumental in this application and, if organized as a crowdsourcing initiative, it can be an example of CI application for cultural heritage purposes. However, the majority of cultural heritage preservation projects involve the financial and operational capacity of the relevant responsible bodies such as ministries. The public value that can be created, apart from preservation of cultural heritage, is also aesthetic, since cultural heritage sites are usually considered to be visually and aesthetically appealing.

The potential to generate public value at both a micro and a macro level is also significant in tax and land policy. VGI has been portrayed as a means to increase data availability on land and other assets that individuals possess. This informs both local and national governments with regards to the assets of each individual for two purposes - first, to develop social policies such as social housing and the second - to tax individuals, so that less cases of tax evasion occur. Correspondingly, this implicates data that are collected at a local level, usually applying citizen science methodology. Data collected through citizen science are then transferred to the Ministry of Finance. The public values associated with the use of TTEs in this policy are efficiency, as well as accountability.

The last policy that is applicable to coordination between micro and macro level of governance as identified by this study encompasses human rights. CI and open data, in the form of citizen science initiatives such as data commons, can be used both to understand how citizens perceive the adoption of technology from the public sector and to what extent it ensures their personal dignity, but also how emerging technologies such as AI and machine learning are addressing (or not) diversity, equity and justice aspects of our society. Hence, TTEs have the potential to also generate public value related to humanitarian/societal causes.

Finally, there is a policy that covers only the macro level. This is the freight and long-distance transport policy. Tracking emissions using open data on the emissions of the different transport routes and exchanging data between governmental agencies through blockchain can help increase transparency and understand the bigger picture with regards to the contribution of long-distance and freight transport in the overall environmental pollution. This is related also to sustainability.

6. Limitations

This study has several limitations. The first is related to the choice of public value frameworks used in this study to explore the potential of TTE for public value generation. Several frameworks exist, having elements going beyond those covered by used framework, some of which could be useful to assess public value generation potential of TTEs, e.g., recreational or historical values as comes from (Zhang et al., 2024). These values, however, seem to have a low probability of being generated by TTEs and, thus, were not taken into account in this study.

Another limitation lies in the applicability of the results. The majority of the cases found in literature, where a convergence of PDEs and 4I artifacts has the potential to generate public value, are conceptual. Hence, it is recommended that different case studies are developed. Case studies should include interviews with relevant stakeholders to explore how the concept of triple transition ecosystems could be operationalized, what its actual potential to generate public value is, and what the main obstacles are.

Finally, there are public values that are not distinguished in literature, such as accountability and transparency. Accountability focuses on the ownership and responsible behavior and, in the context of open data, is related to ensuring that data privacy regulations are being taken into consideration. In some cases, this is rather challenging, as datasets possess sensitive data, such as personal information of citizens, but also data that is important for reusability services, such as health-related epidemiological data that are crucial to inform decision-making. To this end, blockchain technologies can be used in combination with PDEs to ensure anonymity and respect towards data privacy, however, so far literature has not addressed accountability alone.

7. Conclusion

In this study we introduce a concept of TTE that builds upon two complementary concepts of PDEs and the 4I paradigm, the call for which has been made by previous research. As a new concept, knowledge on the potential of TTEs as a combination of the above for the use in the public sector, types of policies it can affect and the kind of public value it can create is limited. The results of this study reveals that there is potential for the TTE to generate public value across ministries and agencies generating public value ranging from sustainability to transparency, accountability, efficiency and innovation. Nonetheless, development of pilot projects and operationalization of TTEs is essential to comprehend whether the conceptual cases found in literature can have the expected impact.

Acknowledgement

- **Funding or Grant** : This work was supported by the Estonian Research Council grant "Developing human-centric digital solutions" (TEM-TA120) and the Mobility Grant of the Estonian Doctoral School.
- **Contributor Statement***: Describe properly all author contributions and all types of contributions) see Policies (tudelft.nl)
- **Use of AI***: During the preparation of this work, the authors used ChatGPT to adjust the text for language and tone. After using this tool/service, the authors reviewed, edited and validated the outcome, and take full responsibility for the content of the publication.
- **Conflict Of Interest (COI)***: There is no conflict of interest.

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