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Characterizing the Role of Geospatial Science in Digital Twins

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Abstract: Delivering value from digital concepts such as Digital Twins is necessary to address systemic national and global issues, such as achieving Net Zero. However, there is still a lack of consensus over what a Digital Twin (DT) is and efforts to clarify this do not consider the Geospatial perspective. With the aspiration for national- and international-scale DTs, it is important that the Geospatial community understands its role in supporting the realisation of the value of these DTs. Here, a systematic literature review is used to gather DT case studies that use, or are inferred to use, elements of the Geospatial discipline. A total of 77 DT case studies about smart cities, manufacturing, energy, construction and agriculture are reviewed in full, and 24 Geospatial DT dimensions are defined and then compared with existing DT dimensions. The results indicate a considerable use of Geospatial Science in DTs that is not explicitly stated, meaning that there are possibly missed opportunities for collaboration between the Geospatial and DT communities. We conclude that the role of Geospatial Science in DTs is larger than stated and needs to be understood further.

Keywords: digital twin; geospatial; characterization; dimensions

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1. Introduction

Addressing systemic issues of global and national scale, such as reaching Net Zero, requires novel solutions and approaches. Digital approaches—amongst others—provide possible means of tackling these issues [1].

In recent decades, the combination of automated, more intelligent engineering systems and the demand to track products throughout their life cycle eventually led to the advent of a concept called the "Digital Twin" (DT). A DT can be conceptualised as "a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems" [2] (p. 2). The idea of a DT first emerged in a 2002 lecture on product lifecycle management (PLM) by Michael Grieves [3], where the idea of a DT was termed as the "conceptual ideal for PLM"; however, it was not until 2011 that the term Digital Twin was coined [4]. Given the origin of the DT in the context of PLM, applications of DTs were mostly confined to the automotive, aerospace and manufacturing industries [5,6].

More recently, the application domains of DTs have broadened considerably [7], and they are now being developed beyond the factory floor to address systemic issues of global and national scale, like achieving Net Zero [8]. In urban environments, for example, DTs are being used to improve urban planning [9], to better manage energy demand and use [10], to deal with more frequent and dangerous natural hazards [11] and to enable smarter cities where sustainability is forefront [12]. DTs also exist in the rural domain to increase efficiency and yields in agriculture and farming [13]. Other DT application domains include medicine and healthcare [14], construction [15] and engineering [16].

What a DT is and what it does vary considerably depending on the application domain [17], and as Jones et al. [18] state, this variation risks diluting the concept and the value it can deliver altogether. This ambiguity has meant that there is a need to distinguish among types of DTs [19], understand those that are effective and ineffective [20] and ultimately strive for a "consolidated and consistent view on what the DT is" [18] (p. 1). The Gemini Principles from the Centre for Digital Built Britain clearly state that DTs must have a clear purpose and lead to value creation [21].

Alongside DTs, Geospatial Science is a digital discipline that has contributed immensely to addressing systemic global issues [22–26]. Having been maturing as a discipline for several decades (first emerging in the 1960s [27]), the application of Geospatial data and approaches to improve decision making is now widely used to address different problem areas, for example, improving hazard risk assessments [22], enabling smart urban development [23] and better land use optimization [24].

The term "Geospatial" can be used to refer to different aspects of the discipline but predominantly refers to the use and aspects of Geographic Information Systems (GISs). For example, the definition of a GIS in Duckham et al. [28] highlights different aspects of Geospatial Science, i.e., capture, modelling, storage, retrieval, communication, sharing, manipulation, analysis, presentation and exploration with respect to geographically referenced data. In addition, there are non-technical aspects to consider, such as the Geospatial community made up of professionals and organisations working in the Geospatial discipline. In this study, the term Geospatial is used frequently and refers to all of these aspects. Where one specific aspect is discussed, this will be clearly stated.

The application of Geospatial Science within DTs is clear in several application domains, primarily in the urban context [29–31], where 3D Geospatial data are used to virtually represent city objects such as buildings and their surrounding environment [32]. Despite this, the broader role of Geospatial Science in DTs is still not well understood [33]. This has meant that the Geospatial community are unaware of how to engage with DT initiatives [33], and vice versa, the potential added value of Geospatial to DT applications remains invisible. Nonetheless, there is an opportunity within DTs to highlight the relevance, added value and role of Geospatial Science [34].

Existing classifications of DTs fall into two groups, those that seek a generalized, application-domain agnostic view of DTs [2,18,35,36] and those that classify application-specific DTs [10,13,19,20,37,38]. These classifications use different methods (discussed further in Section 2) to identify key dimensions and characteristics of DTs. The resulting dimensions and characteristics of DTs vary depending on the application domain in question [35].

As far as we are aware, there has been no cross-domain characterization of DTs using both DT and Geospatial dimensions. We hypothesise that whilst there are obvious and clearly stated uses of Geospatial Science in DTs, we believe there are also less obvious and unstated uses of Geospatial Science in DT examples. This is a problem, since such implicit use of Geospatial Science hinders the use of knowledge and solutions from the Geospatial discipline in its full potential. Awareness of the Geospatial dimensions is not a new issue, and work carried out by the UK's Geospatial Commission highlights this. A market-sizing exercise conducted by Frontier Economics on behalf of the Geospatial Commission in 2020 highlighted the widespread lack of awareness about the benefits of using Geospatial Science in different workflows [39].

By uncovering the unstated, implicit uses of Geospatial Science, the Geospatial community can better understand how they can add value to DT initiatives and ultimately collaborate more effectively to solve systemic national and global issues, like reaching Net Zero.

This study aims to progress the understanding of the role of Geospatial Science in DTs, focusing on two aspects which are stated as the following research questions:

- How explicit is the use of Geospatial Science in DTs?
- What are the Geospatial dimensions of DTs?

We answer these questions and achieve our aim by conducting a systematic literature review of the DT corpus with the aim of specifically identifying DT case studies that have

Geospatial aspects, thereby focusing on real-world examples of DTs rather than the DT concept as a whole. By doing so, we aim to uncover uses of Geospatial Science that are not clearly stated (defined as "implicit"). We define a set of Geospatial terms that we consider to clearly refer to Geospatial Science and another set of terms that implies but does not confirm the use of Geospatial Science. From a systematically derived set of Geospatial DT case studies, we then define a set of Geospatial dimensions and compare these with existing DT dimensions.

The remainder of this document is structured as follows: Section 2 provides a review of existing classifications of DTs, as well as reviewing the state of the art in the use of Geospatial Science in DTs. Section 3 describes the methodology for the systematic literature review and the characterization. Section 4 provides a summary of the search results and the resulting characteristics. This is followed by a discussion on the role of Geospatial Science in DTs and future work in Section 5. Section 6 contains our concluding remarks.

2. Related Work

The cross-domain growth of the DT concept has led to inconsistencies in what a DT is (i.e., its components) and what it does (i.e., its features). Most importantly, this has resulted in a lack of focus on value creation and defining a clear purpose of the DT, a core part of the original concept defined by Grieves [2,40]. Consequently, there has been a need to define a more consistent view of DTs [18] and distinguish among different types of DTs [10].

Classifications are used to reduce complexity and enable the identification of similarities and differences among cases. The two primary methods of classification are typology and taxonomy [41], as highlighted in Figure 1. Typology is a qualitative method that focuses on conceptually defining types by using a few characteristics. Taxonomy, on the other hand, is a quantitative method where categories are derived empirically by using multivariate techniques [42], such as cluster analysis [41]. Regardless of the method used, it has been noted that classification is an important element of understanding a concept [42].

Bailey [41] notes how classifications are only as good as the dimensions used to distinguish cases. As a result, defining a set of dimensions is the first step in any classification [41]. The terms "characteristic" and "dimension" are used interchangeably in the literature to refer to these distinguishing variables. In addition to taxonomy and typology, characterisation refers to methods where a series of characteristics are defined [18]. In this study, we adopt the term "dimension" to refer to any aspect of a DT, including a characteristic.

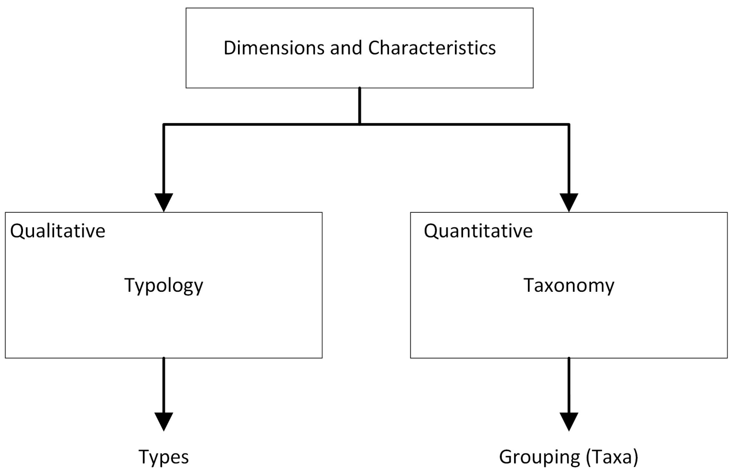

Figure 1. The two main methods of classification [41].

2.1. Classifications of Digital Twins

Several studies focus on characterising and classifying DTs by using frameworks [10,36,37,43–45], taxonomies [19,35], maturity models [20] and typologies [9,13,19,38].

2.1.1. Dimensions

Grieves [40] was the first to define a set of dimensions for DTs, following the introduction of the DT concept in a lecture on PLM in 2002 [3]. The dimensions defined were Physical Products, Virtual Products and Connections between Virtual and Physical Products. Physical Products refers to a physical product in real space (in this case, a product on the factory floor). Virtual Products is defined as "rich representations of products that are virtually indistinguishable from their physical counterparts" [40] (p. 1). Connections between Virtual and Physical Products refers to the exchange of information and data between the physical and virtual dimensions. Since this original characterization, there have been several different approaches to enhancing and adapting the list of dimensions. Approaches include those that have focused on defining generic, cross-domain dimensions [2,18,45,46] and those that have focused on defining DT dimensions within a particular application domain [19,31,35,47]. Table 1 provides a summary of the resulting DT dimensions.

Table 1. Summary of Digital Twin (DT) dimensions identified in the literature.

Meta-Dimension	Dimension
Physical World	Physical Entity [18,20,40,43,46] Physical Environment [18,20] Physical Process [2,18,20] Physical System [2]
Virtual Representation [40]	Virtual Entity [18,43,48] Virtual Environment [2,18] Virtual Process [2,18] Virtual System [2]
Connection [43]	Physical-to-Virtual Connection [2,18,43] Virtual-to-Physical Connection [2,18,43] Level of Integration [13,20,31,35,46,48] Twinning Rate [13,18,20,31,35]
Data [43]	Formats [36] Categories [36] Sources [19,20,31,36] Acquisition [19,44] Governance [19]
Fidelity [13,18,20,46,48]	Accuracy [35]
Services [43]	Analysis [13] Interface [20,35]
Context	Purpose [31,35,46] Application Domain [20,46]

In the Manufacturing and Production application domain, the three original dimensions defined by Grieves [40] were extended by Tao et al. [43] in a five-dimensional framework to include the dimensions Services and Data. The Services dimension describes the functions of the DT, such as prediction or simulation. The Data dimension describes the data obtained from the physical and virtual aspects as well as data from the Services model, domain knowledge and fused data.

Kritzinger et al. [47] focused on classifying the Level of Integration between the physical entities and virtual models and defined three characteristics for this dimension: Digital Model (no automated data exchange), Digital Shadow (automated data exchange in one direction from physical entity to virtual model) and Digital Twin (automated data exchange in both directions between physical entity and virtual model). Here, it is noted that most of the publications reviewed were either classed as Digital Shadows and Digital Models. However, this characterization was conducted in the Manufacturing application domain, so it may not necessarily be applicable to other DT application domains.

More broadly than manufacturing and production, Enders and Hoßbach [46] reviewed 87 publications in the industrial sector as a whole and proposed six dimensions: Industrial Sector, Purpose, Physical Reference Objects, Completeness, Creation Time and Connection.

Six studies reviewed focused on a cross-domain characterisation of DTs [2,18,19,35,36,45]. Jones et al. [18] used thematic analysis on 92 publications from the last 10 years to provide a detailed characterisation. The results highlighted twelve dimensions: Physical Entity, Virtual Entity, Physical Environment, Virtual Environment, Fidelity, State, Parameters, Physical-to-Virtual connection, Virtual-to-Physical Connection, Twinning and Twinning Rate, and Physical Process and Virtual Process. Similarly, VanDerHorn and Mahadevan [2] reviewed 46 definitions of DTs and proposed three meta-dimensions and eight characteristics (also highlighted in Jones et al. [18]). These are Physical Reality (Physical System, Physical Environment and Physical Process), Virtual Representation (Virtual System, Virtual Environment and Virtual Process) and Interconnection between the Physical Reality and Virtual Representation (Physical-to-Virtual connection and Virtual-to-Physical Connection). The dimensions Parameters and State in Jones et al. [18] were derived from state space modelling terminology and are also adopted in VanDerHorn and Mahadevan [2].

Conversely, a taxonomic method was used by van der Valk et al. [35] to identify a set of DT dimensions. In van der Valk et al. [35], eight dimensions were identified: Data Link, Purpose, Conceptual Elements, Model Accuracy, Interface, Synchronisation, Data Input and Time of Creation. From a terminological perspective, these dimensions vary from those highlighted in Jones et al. [18] and VanDerHorn and Mahadevan [2]; however, they often refer to the same dimension. For example, Data Link in van der Valk et al. [35] refers to whether the link between the virtual representation and its physical counterpart is one-directional or bi-directional. The Physical-to-Virtual Connection and Virtual-to-Physical Connection dimensions in Jones et al. [18] and VanDerHorn and Mahadevan [2] refer to the same aspect. van der Valk et al. [19] extended the taxonomy defined in van der Valk et al. [35] to derive a set of dimensions specific to electrical and mechanical engineering. The dimensions Data Acquisition, Data Source, Data Governance and Interoperability were added to the original taxonomy in van der Valk et al. [35].

Barth et al. [36] proposed a set of three primary dimensions and nine sub-dimensions by using an ontology and conceptual framework. These dimensions are Data Resources (Data Sources, Data Categories and Data Formats), External Value Creation (attributes of the services as basis of value propositions, level of smartness of connected products, actors on the different levels of the ecosystem) and Internal Value Creation (lifecycle phase of products, Product Management Levels and different generations of both). Similarly to van der Valk et al. [19], the inclusion of Data dimensions enables easier deduction of the data requirements for specific DT applications. In addition, the focus on value creation is a useful method for communicating DTs to internal and external stakeholders, an existing barrier to DT adoption [49].

The final cross-domain characterization is Newrzella et al.'s [45]. This study reviewed five DT classification models and subsequently proposed a five-dimensional model to improve understanding of cross-industry DTs. This five-dimensional model is different from the model proposed in Tao et al. [43] and contains the dimensions Scope of the Physical Entity, Feature of the Physical Entity, Form of Communication, Scope of the Virtual Entity and User-Specific Outcome of Value Created.

In the application-specific cases, Agnusdei et al. [44] proposed a three-axis model for DTs in the safety application domain with three meta-dimensions and nine corresponding dimensions. The dimensions proposed here are much more application domain-specific, such as HMI Risks, Human-Based Risks and Machine-Based Risks. The other dimensions relating to Data Processing and Data Acquisition are reflected somewhat in other studies [31,35,36]. This model is an example of a combination of generic dimensions and application domain-specific dimensions and could be applied in other application domains.

Yu et al. [10] defined a framework for classifying DTs in the energy sector with five dimensions: Looks-like Attribute, Behaves-like Attribute, Connected-to Attribute, Physical

Scale and Time Scale. Within each, there are associated characteristics defined. For example, the Looks-like dimension can have the values 1D, 2D or 3D representation and the Physical Scale can be Nano, Micro, Meso or Macro. The Connected-to attribute suggests that a DT does not necessarily have a two-way direct data flow between the physical and virtual parts, contrary to Kritzinger et al. [47]. Conversely, Uhlenkamp et al. [20] classifies DTs by using a maturity model with seven dimensions: Context, Data, Computing Capabilities, Model, Integration, Control and Human–Machine Interface. DTs that interpret and exploit unstructured data, for example, are recognized as having greater maturity. The benefit of this approach is the ability to evaluate effective and less effective DTs more easily. Autiosalo et al. [37] also used a framework approach but focused on features of the DT which can be used to distinguish DTs.

2.1.2. Typologies

Several typologies have also been developed to distinguish DTs. Our review of DT typologies across different application domains identified 38 distinct types of DTs (Table 2).

Table 2. Types of DTs.

Source	Types
[18,50]	Digital Twin Prototype Digital Twin Instance Digital Twin Environment Digital Twin Aggregate
[13]	Imaginary DT Monitoring DT Predictive DT Prescriptive DT Recollection DT Autonomous DT
[19]	Basic DT Enriched DT Autonomous Control Twin Enhanced Autonomous Control Twin Exhaustive DT
[38]	User-centric DT Communication-centric DT Collaboration-centric DT Content-centric DT Partial DT Historic DT Heritage DT Fused DT Evolved DT During-time DT Cognitive DT Clone DT Augmented DT
[46]	Control DT Simulation DT
[14]	Human DT (Whole-Body, Single-Organ and Cellular-Level Systems)
[31]	Urban DT
[9]	Urban Planning DT (Static and Managerial, Dynamic–Evolutive and Collaborative, Dynamic–Evolutive) City-State DT City-Scale DT

Some of the first DT types were defined in Grieves and Vickers [50] in the context of product lifecycle management. A Digital Twin Prototype, for example, is defined as a virtual representation of a prototype, while a Digital Twin Aggregate is defined as the sum of all DT instances [50].

More recently, in the Agriculture application domain, Verdouw et al. [13] also developed a typology based on product lifecycle but also included the role of the Internet of Things (IoT) and other functions of the DT. The typology comprises six distinct types: Imaginary DT, Monitoring DT, Predictive DT, Prescriptive DT, Autonomous DT and Recollection DT. In the electrical and mechanical engineering domain, van der Valk et al. [19] used cluster analysis to define a set of archetypes based on the mandatory characteristics defined in the taxonomy highlighted previously. The five resulting archetypes reflect DT maturity from Basic DTs to Exhaustive DTs. The distinction is that an Exhaustive DT has a Machine-to-Machine Interface and the ability to use pre-processed data and to integrate with other downstream systems in addition to the physical entity itself. It is noted that Exhaustive DTs are challenging to realize. Another type of DT commonly used is the Urban DT [31], which is discussed further in Section 2.2. Caprari et al. [9] developed a set of DT types for the urban planning application domain by using a critical comparative analysis of six case studies. The dimensions of an Urban DT are described as Scalability, Predictability, Integration and Cooperation/Accessibility [9]. Based on this, the three types defined for urban planning are Static and Managerial, Dynamic–Evolutive, and Dynamic–Evolutive and Collaborative.

The classifications described in the sections above are summarised in Table 3 and are grouped by application domain.

Table 3. Summary of characterization and classification approaches in the DT literature.

Method	Sources	Application Domain
Dimensions	[2,18,45,46]	Cross-domain
	[40]	Manufacturing and Production
	[31]	Cities
Framework	[45]	Cross-domain
	[43]	Manufacturing and Production
	[37]	Mechanical Engineering
	[44]	Safety
	[10]	Energy
Ontology and framework	[36]	Cross-domain
Maturity model	[20,47]	Manufacturing and Production
Taxonomy	[19,35]	Cross-domain
Typology	[46]	Manufacturing and Production
	[19]	Mechanical Engineering
	[13]	Agriculture
	[38]	Cultural Heritage
	[9]	Urban Planning

2.2. *Role of Geospatial Science in Digital Twins*

In addition to the literature on the classification and characterisation of DTs, there is also a body of research that provides some insights into the relationship between Geospatial Science and DTs, sometimes described as Geospatial DTs [51]. Terminology relating to the role of Geospatial Science in DTs is discussed later in the section. Figure 2 presents this idea of a Geospatial DT as a combination of aspects of the Geospatial discipline with those from the DTs.

The role of Geospatial Science in Digital Twins is most explicit in the context of DTs for urban problems. Urban DTs emerged from the shift from twinning products to twinning cities [52]. Cities have been a focus for the Geospatial community for several decades [53] in the form of 3D City Models (3DCMs), Building Information Modelling (BIM), Spatial Data Infrastructures (SDIs) and smart cities. Despite this, there is inconsistency in the relationships among DTs, 3DCMs, SDIs and BIM [31]. For example, they reference different time scales. As a system of systems, cities are highly complex environments with a huge number of data generated at a scale that is not comparable with a single product or system. It has been noted that in fact City DTs (and Urban DTs) should be treated entirely separately from other application domains [17].

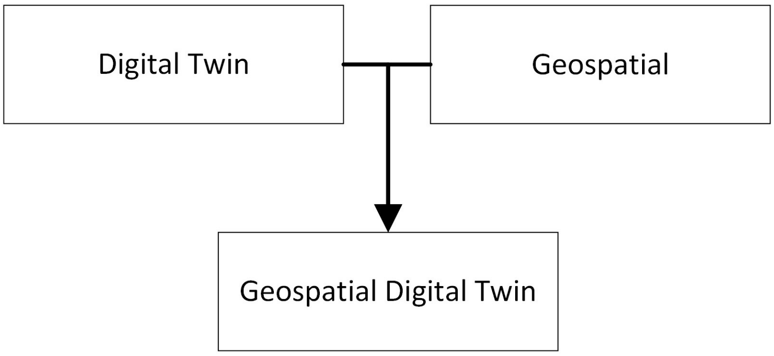

Figure 2. Combining Geospatial Science with DTs to form Geospatial DT.

Jeddoub et al. [31] distinguished 3DCMs, City Information Models (CIMs) and SDIs from City DTs. The results of a survey and a literature review indicated that 3DCMs are widely accepted to be a basis for building a City DT, with the spatial and temporal scales in DTs being larger than those in 3DCMs. Similarly, a CIM was seen as a starting point for a City DT, later to be enhanced with the IoT and real-time bi-directional data integration. Most participants also agreed that an SDI is a foundation for a City DT for the sharing of Geospatial information and interoperability. However, some participants disagreed that DTs should extend from existing SDIs and are not necessarily Geospatial models. As described in Section 3.1, Jeddoub et al. [31] defined a set of Geospatial dimensions to distinguish City DTs based on, for example, scale (Geographic Extent), Data Sources and Level of Detail (Generalization). The focus of the study, however, is limited to cities, and the role that Geospatial Science has more broadly in DTs is not discussed or classified.

Geospatial Science has been referred to in the context of DTs in a number of ways in the literature. In Jones et al. [18], for example, location is proposed as a parameter (the types of data transferred between entities) of DTs. In this sense, the geographic location of the physical entity (and environment) is considered an important data type which enables the entity and environment to be visualized on a map, as described in Ellul et al. [33]. In addition, the parameter form (the entity's geometric structure) may also have a Geospatial element, particularly in the context of Urban DTs, where the entity may be a building.

Caprari et al. [9] highlighted the role that Geospatial Science plays in the development of virtual representations themselves. In part, this is due to the increasing availability of Geospatial data in recent years allowing for more complex and dynamic systems to be represented [31].

In another context, Geographic Information Systems (GISs) and Global Positioning System (GPSs) are referred to as enabling technologies and tools for data acquisition and transmission [16,48,54], and the map is referred to as a key technology for visualization [54,55]. Moreover, Park and Yang [55] highlighted how Geospatial professionals can contribute analytics methods to DTs.

In terms of the IoT, as networks of connected sensors, it is noted how these high-quality temporal data are often not used due to a lack of spatial context [56]. Qi et al. [54] also highlighted a similar challenge within DTs of integrating models with different spatial and temporal scales.

Ellul et al. [33] discussed the role of Geospatial Science, and more specifically, location data in DTs based on insights from a survey of participants from National Mapping and Cadastral Agencies (NMCA) and industry professionals. The survey highlighted similarities between challenges faced in the Geospatial community and those in the DT community. For example, interoperability, data management and governance were noted particularly as shared challenges that the Geospatial community has made progress in addressing. The hypothesis presented in the paper is that location data could be important for the physical–digital linking of heterogenous data in DTs.

In terms of terminology that describes the role of Geospatial Science in DTs, the term Geospatial Digital Twin was used by Döllner [51] in the context of Machine Learning (ML) for 3D point clouds. In this case, Geospatial DT is defined as a "means for monitoring, visualizing, exploring, optimizing and predicting behavior and processes related to the corresponding physical entities" (p. 18). Similarly, Rathor et al. [57] used the term Geospatial DT to describe "a digital replica of a spatial entity where ML and DL techniques are used for interpretation, analysis and organization of 3D point clouds" (p. 3). On the other hand, Ellul et al. [33] uses the term Location-Enabled DT to highlight location data's enabling role for the DT to fulfil its purpose. In Lehner and Dorffner [58], a DT of the city of Vienna, Geo-, was added to the Twin to highlight the particular focus on the geometric aspect of semantic objects. Moreover, Jeddoub et al. [31] used the terms Geospatial DT and Spatial DT to highlight the fact that Geospatial Science provides the spatial context of the entities being represented in the DT.

Whilst these terms have been used to emphasize or highlight the role of Geospatial Science in DTs, there is a lack of consistency in the different motivations for using them, as well as no clear characterization or distinction of DTs that involves Geospatial Science. There is, therefore, a need to clarify the Geospatial dimensions of DTs across application domains and, more broadly, promote a discussion on the role that Geospatial Science plays in DTs.

3. Materials and Methods

A systematic literature review (SLR) was preferred to a bibliometric analysis given the desire to understand the various dimensions of DTs in detail. The SLR was based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [59] to ensure that the approach was transparent and reproducible [60].

An eight-step methodology (Figure 3) was used to define a set of Geospatial dimensions of DTs. These steps are as follows:

1. Select the application domains;
2. Define the Geospatial terms for searches;
3. Conduct a database search;
4. Filter the results;
5. Perform forward and backward searches;
6. Fully review the papers;

7a. Define the Geospatial DT dimensions;

7b. Iterate the Geospatial terms for searches;

8. Map the Geospatial DT dimensions against the existing DT dimensions.

Sections 3.1–3.7 describe these steps in more detail.

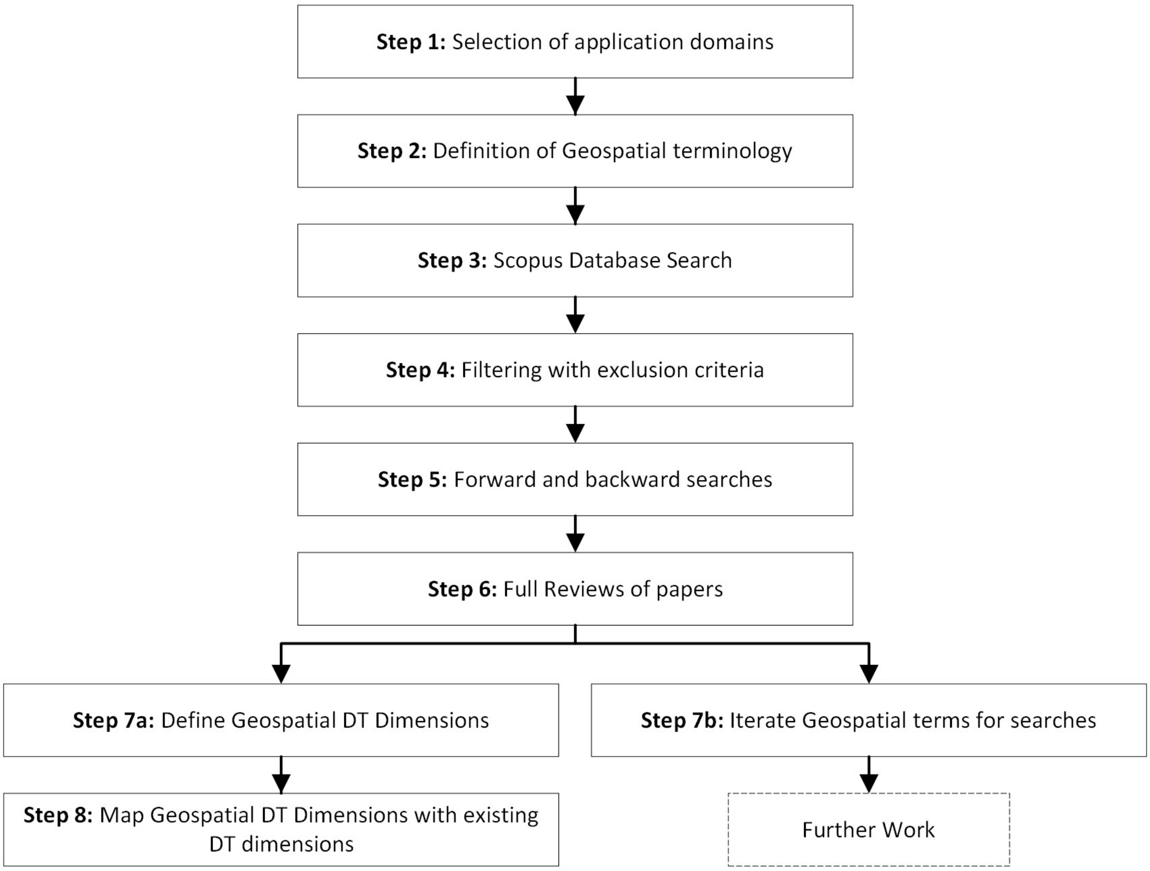

Figure 3. Eight-step methodology used for this systematic review.

3.1. Step 1: Selection of Application Domains

DTs exist across different application domains, resulting in different perspectives and implementations of the concept [17]. To understand the role of Geospatial Science in DTs, we sought to obtain a set of DT case studies that represented a cross-section of the application domains. Numerous assessments of DT application domains exist [16,20,46,54,61,62]. We used the table of application domains in [8], which ranks the application domains based on the volume of DT research relating to sustainability, to select the application domains for this study. We selected the top 5 application domains and grouped them together as follows:

- Manufacturing, Production and Aerospace;
- Smart Cities and Urban Applications;
- Construction;
- Energy;
- Agriculture.

3.2. Step 2: Definition of Geospatial Terms for Searches

To uncover the uses of Geospatial data in DTs, our search strategy (described in Section 3.3) uses a set of terms to return explicit and implicit references to the use of Geospatial data in any particular DT publication. This method assumes that the use of Geospatial data in DTs is not always clearly stated. Explicit is defined as follows:

> "…distinctly expressing all that is mean; leaving nothing merely implied or suggested" [63]

On the other hand, implicit is defined as follows:

> "…capable of being inferred from" [63]

Therefore, within this research, we define explicit Geospatial language as terms that clearly express the use of Geospatial Science in the DT. Moreover, we define implicit Geospatial language as terms that suggest but do not confirm the use of Geospatial Science in the DT. We define a set of terms (Table 4) within each of these groups by using a combination of crowdsourcing, a review of the GIS dictionary of terms [64] and our own experience in the Geospatial discipline. We acknowledge that these lists are incomplete, subject to interpretation and include an element of fuzziness. As one example, some terms can have different spellings depending on whether British English or American English is used. These differences are not considered in this paper but will be considered for future work. In addition, we expect the lists as a whole to be iterated in future work. In the context of this study, however, the terms have progressed our understanding of the role and use of Geospatial Science in DTs.

Table 4. Explicit and implicit Geospatial terms.

Explicit	Implicit
Geospatial; GIS; Geographic Information Systems; Geography; Geo-visualization; Geoinformation; Spatial analytics; Geo-AI; Spatio-temporal; GeoBIM; 3D City Model; Geomatics; Surveying; GNSS; Geo-computation; Geocode; Georeference; Digital Elevation Model; DEM; Digital Terrain Model; DTM; Geodatabase; Geodesy; Geodetic; Coordinate System; Photogrammetry; Cartography	Location; Spatial; Region; Street; Position; Precinct; District; Neighbourhood; BIM; Internet of Things; City Model; 3D Model; GPS; Augmented Reality; AR; Virtual Reality; VR; Land; Cadastre; Coordinates; County; Datum; Origin-Destination; Route; Sensor; Terrain; Topology; Remote Sensing

3.3. Step 3: Scopus Database Search Parameters

We conducted our search in the Scopus database [65] in the period January 2024–February 2024. Given the exponential increase in the DT literature in recent years [2], we focused our search on the last 5 years (2019-present). Table 5 highlights the search parameters used, notably ensuring that the term Digital Twin is present in the source title and keywords. In addition, the explicit and implicit Geospatial terms (Table 4) were searched for in the titles, abstracts and keywords. These terms are included in both acronym form (where applicable) and in full. Conference papers were included in the search as suggested by [66].

Table 5. Scopus database search parameters.

Search Parameters
2019–Present
Digital Twin or Digital twin or digital twin in title
Digital Twin or Digital twin or digital twin in keywords
Application Domain in keywords
Explicit and Implicit Geospatial terms in title, abstract or keywords
Case Study or Case study or case study in title, abstract or keywords
Language is English

The goal of our search was to obtain two sets of publications for each application domain, where in the first, the use of Geospatial Science is clearly expressed (explicit), and in the second, there is a suggestion that Geospatial Science is used. Therefore, we sought to obtain 10 datasets. We made use of the AND NOT operator in Scopus to ensure that explicit terms were excluded from implicit searches. We conducted searches with and without the term case study to understand the broader landscape and then narrowed the search to actual DT case studies that could be used for the characterisation. We also ran additional searches based on the most frequently identified implicit terms to understand their role in the corpus. In all cases, only the first 20 results sorted by relevance were considered, given the breadth and depth of the systematic review.

3.4. Step 4: Filtering

We carried out two stages of filtering to reduce the number of publications to a number that could be reviewed in full. During the first stage of filtering the initial search results, we used a set of exclusion criteria to either remove the publication from the dataset or re-assign it to another group (both application domain and/or explicit/implicit). We sought to obtain a set of publications that related to actual implementations of DTs, rather than a conceptual discussion. We conducted the first round of filtering by using the exclusion criteria described in Table 6 during an abstract review of the results from Step 3.

Table 6. Exclusion criteria for abstract reviews in Step 3.

Situation	Action
Publication is too conceptual (i.e., no clear DT case study)	Reject
Publication is a false positive (i.e., the explicit/implicit terms relate to something other than the Geospatial meaning)	Reject
Publication related to an application domain not considered in this study	Reject
Publication more appropriate to another application domain	Re-assign to more relevant group

During the second stage of filtering, we ran a word search on the full publications by using a subset of the explicit and implicit terms. We did so for two reasons. Firstly, to identify uses of explicit and implicit terms in the whole publication instead of just the title, abstract and keywords and ensure that the publication is in the most appropriate group. Secondly, to ensure that explicit and implicit references were in the context of the methodology or case study presented instead of just a related-work reference. Table 7 describes the exclusion criteria used for this round of filtering.

Table 7. Exclusion criteria for abstract reviews in Step 4.

Situation	Action
Explicit/implicit term not used in the context of the methodology or case study	Reject
Explicit term identified (in the context of the methodology or case study) in an implicit publication	Re-assign to explicit group

The resulting dataset at the end of Step 4 was then taken into the full paper review in Steps 5 and 6.

3.5. Steps 5 and 6: Forward and Backward Searches and Full Reviews

The remaining publications were divided into review papers and articles. As suggested by Webster and Watson [66], a forward and backward search was conducted on these review papers to identify further DT case studies to use in the characterization. The same parameters (Table 5) as the database search were applied to the identified publications for use in the dataset.

The resulting dataset was then reviewed in full for the characterisation in steps 7 and 8.

3.6. Step 7a and b: Geospatial DT Dimensions and Explicit/Implicit Search Terms

During this step, Geospatial DT dimensions were extracted from the case studies based on the identification of Geospatial terms and our experience in the Geospatial domain. We sought to include enough dimensions to allow us to characterize the role of Geospatial Science in DTs. In order to validate the Geospatial DT dimensions that we were defining, we used the definition of a GIS in Duckham et al. [28] presented in the introduction to ensure that there were no aspects of the Geospatial discipline that were not covered. The full definition is the following: "A geographic information system is a computer-based information system that enables the capture and modeling, storage and retrieval, communication and sharing, manipulation and analysis, presentation and exploration of geographically referenced data" [28] (p. 2). The different elements of the definition were treated as Geospatial dimensions and were extracted for comparison with the Geospatial dimensions identified in the application-specific DTs.

In addition, alongside the identification of the Geospatial dimensions, additional explicit and implicit terms were also extracted from the case studies to add to a second iteration of the Geospatial search terms used in this study (Table 8).

Table 8. Updated explicit and implicit Geospatial terms (new terms in **bold**).

Explicit	Implicit
Geospatial; GIS; Geographic Information Systems; Geography; Geo-visualization; Geoinformation; Spatial analytics; Geo-AI; Spatio-temporal; GeoBIM; 3D City Model; Geomatics; Surveying; GNSS; Geo-computation; Geocode; Georeference; Digital Elevation Model; DEM; Digital Terrain Model; DTM; Geodatabase; Geodesy; Geodetic; Coordinate System; Photogrammetry; Cartography; **Geographical scale**; **Heatmap**; **Geopoint**; **Latitude**; **Longitude**; **Euclidean**	Location; Spatial; Region; Street; Position; Precinct; District; Neighbourhood; BIM; Internet of Things; City Model; 3D Model; GPS; Augmented Reality; AR; Virtual Reality; VR; Land; Cadastre; Coordinates; County; Datum; Origin-Destination; Route; Sensor; Terrain; Topology; Remote Sensing; **Positioning**; **Tracking**; **Geometry**; **Localised**; **Topological**; **Direction**; **Site**; **Navigation**; **Localisation**; **Zone**; **Distance**; **Level of detail**; **Adjacent to**; **Near to**; **Masterplan**; **Orientation**; **Land parcel**; **Vicinity**; **Dispersed**

3.7. Step 8: Mapping Dimensions

The Geospatial DT dimensions defined in Step 7 were compared with the status quo on DT dimensions (Table 1). Mapping was conducted in Microsoft Visio [67] between the different dimensions to understand whether there was similarity or not. Those that were deemed to be related were clustered close to one another, and those without a relationship were grouped separately. At this stage, any gaps in the existing DT dimensions based on our Geospatial DT dimensions were then highlighted.

The list of Geospatial DT dimensions and their mapping against existing DT dimensions are presented in Section 4.

4. Results

4.1. Steps 1–3: Paper Retrieval

The results from each state of the systematic review are presented in Figure 4. As a result of this process, 92 publications from five application domains were reviewed in full as part of the characterization.

The initial search for explicit and implicit references to Geospatial Science resulted in 81 and 2269 papers, respectively, across the five application domains. At this stage, the search criteria for case studies were not added. This clearly highlights that there are more implicit references to Geospatial Science than explicit ones in the DT corpus. Figures 5 and 6 highlight the respective proportions of each application domain within the total number of explicit and implicit publications.

The Manufacturing, Production and Aerospace application domain made up 66% of the total number of implicit results, with 1504 papers, followed by Energy, with 380 papers (17%); Construction, with 199 papers (9%); Smart Cities and Urban, with 141 papers (6%); and Agriculture, with 45 papers (2%). In terms of explicit references, on the other hand, Smart Cities and Urban constituted 64% of the total number of explicit results, with 52 papers. This was followed by Energy, with 12 papers (15%); Construction, with 9 papers

(11%); and Manufacturing, Production and Aerospace and Agriculture, tied with 4 papers each (5%).

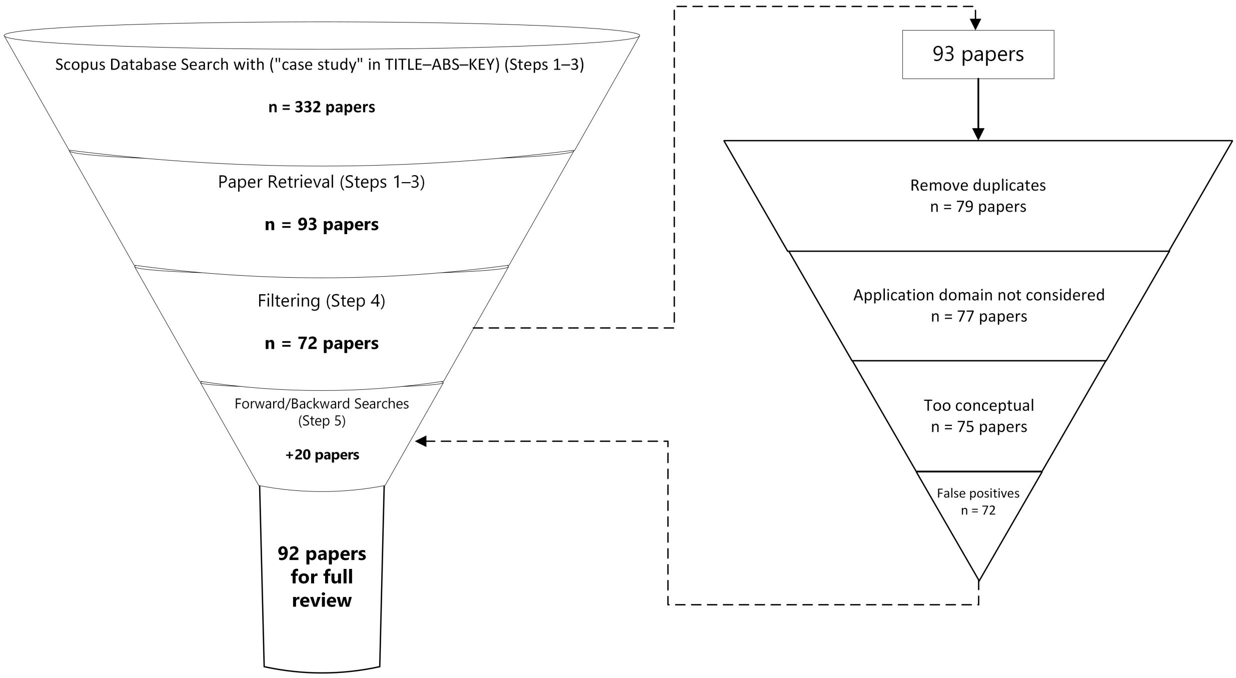

Figure 4. Results of steps 1–5 of the systematic review.

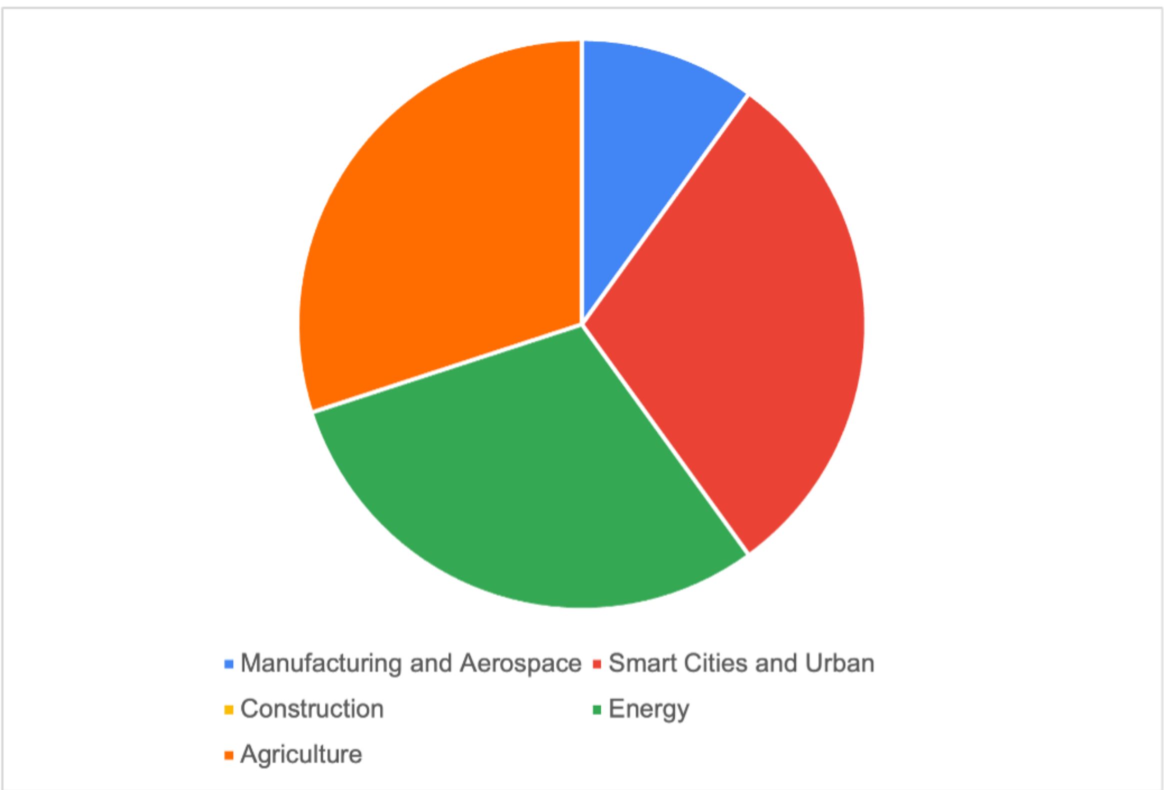

Figure 5. Proportions of papers in each application domain in explicit group.

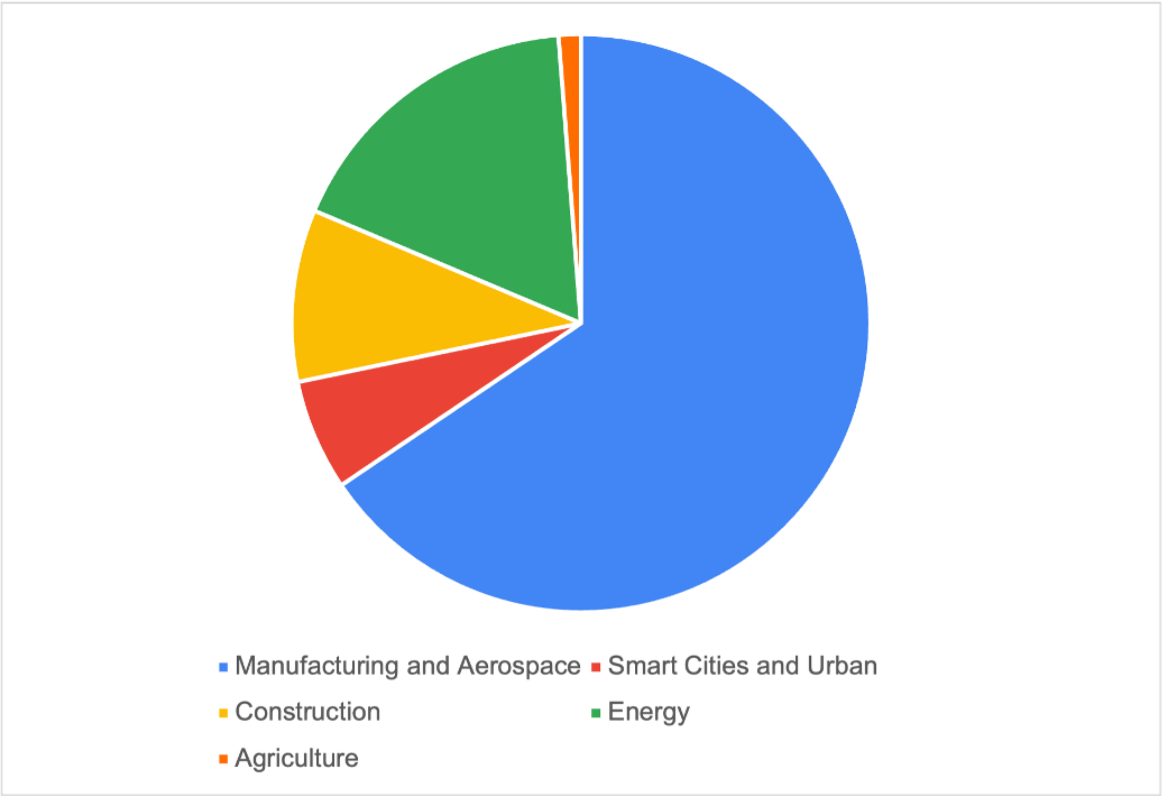

Figure 6. Proportions of papers in each application domain in implicit group.

The three implicit terms that returned the greatest number of papers were IoT, BIM, and Augmented Reality (AR)/Virtual Reality (VR). The proportion of implicit publications in each application domain based on the term IoT was the highest in the Smart Cities and Urban domain, with 72 papers (51%), followed by Energy, with 146 papers (38%); Manufacturing, Production and Aerospace, with 540 papers (36%); and Construction, with 66 papers (33%). Conversely, the proportions based on the term BIM were the highest in Construction, with 61 papers (31%), followed by Smart Cities and Urban, with 12 papers (9%); Manufacturing, Production and Aerospace, with 59 papers (4%); and Energy with 13 papers (3%). Finally, the proportions based on the terms AR/VR were the highest in Construction, with 27 papers (14%), followed by Manufacturing, Production and Aerospace, with 198 papers (13%); Smart Cities and Urban, with 15 papers (11%); and Energy, with 20 papers (5%). These results are presented in a bar chart in Figure 7.

As described in Section 3, the term case study was added to the search parameters to narrow down the results to actual implementations of DTs. Unsurprisingly, this reduced the size of the explicit and implicit results to 10 and 322 papers, respectively (a total of 332 papers was returned in the searches). For the implicit searches, the proportions in each application domain remained largely the same, with only a significant reduction in the number of results (a reduction of 1947 publications). Similarly, for the explicit searches, the number of results was reduced considerably (a reduction of 71 publications), with only three results each in Energy, Smart Cities and Urban and Agriculture. There was only one explicit result in the Manufacturing, Production and Aerospace domain and no results in Construction.

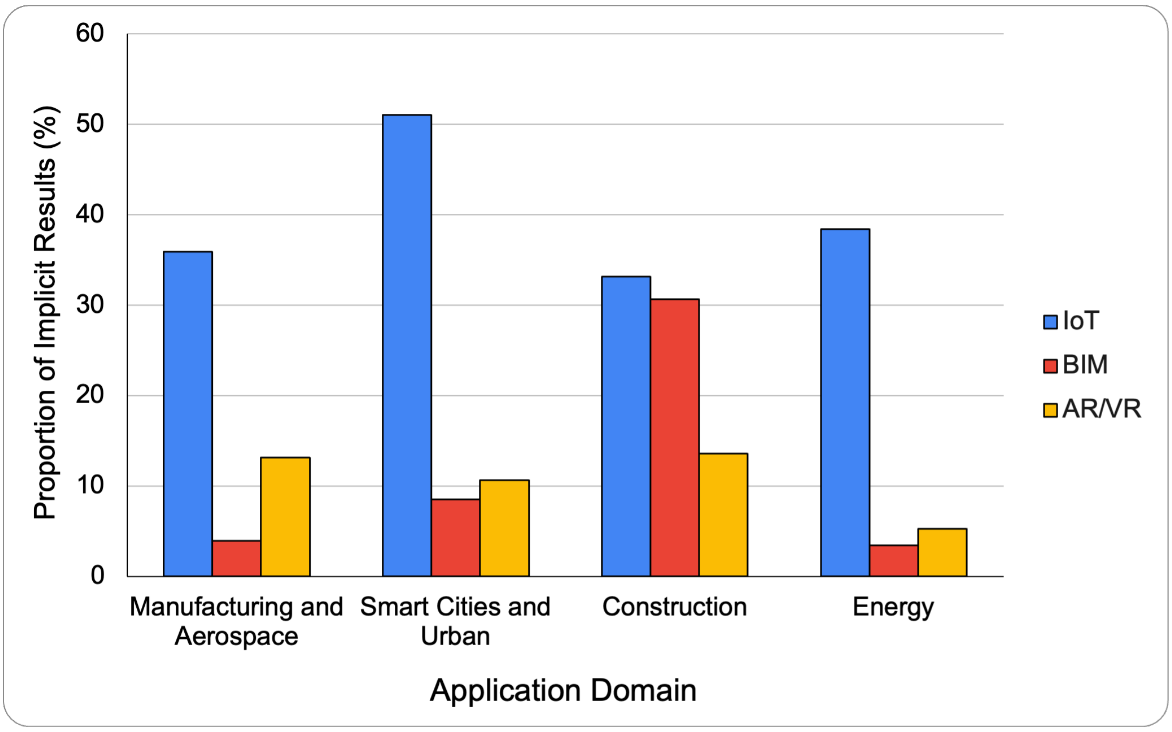

Figure 7. Proportions of occurrence of the terms IoT, BIM and AR/VR in each application domain group.

4.2. Steps 4–6: Filtering, Forward/Backward Searches and Full Reviews

The abstract reviews of the search results reduced the dataset size from 93 publications to 72 publications with 14 duplicates, 2 application domains not considered, 2 deemed too conceptual and 3 false positives on the explicit and implicit terms.

The forward and backward searches on the review papers resulted in an additional 20 papers being added to the dataset, resulting in a dataset of 92 publications for full review. However, after the full reviews conducted in Step 6, a further 15 papers were rejected on the basis of being too conceptual, showing insufficient reference to a particular case study or being a duplicate based on the exclusion criteria described in Section 3.

The resulting set of publications used to extract Geospatial DT dimensions was composed of 77 papers (26 explicit and 51 implicit), which can be found in Table A1 in Appendix A.

4.3. Step 7: Extracting Geospatial DT Dimensions and Additional Explicit/Implicit Terms

A total of 24 Geospatial DT dimensions were extracted from the dataset (Table 9). All of the papers in the dataset, except two, were deemed to reference at least one Geospatial DT dimension. In terms of validating these dimensions with the definition of a GIS in Duckham et al. [28], all elements of the definition are covered by the dimensions in the Geospatial DT dataset.

A total of 27 additional terms were added to the explicit and implicit lists presented in Table 4. The updated list is presented in Table 8 with the new terms in bold. This list will continue to be iterated and developed after this study.

The top three occurring Geospatial DT dimensions across the dataset were Spatio-temporal Data Types, with 63 papers; Locatable Entity, with 53 papers; and Geometric Representation, with 31 papers. The least frequently occurring Geospatial DT dimensions across the dataset were Spatial Data Sharing (one paper), Spatial Data Format (three papers) and Spatial Data Standards (four papers).

In terms of variation among application domains, Spatio-temporal Data Type was in the top three Geospatial DT dimensions in all application domains. Moreover, Locatable

Entity featured in all application domains, except Smart Cities, and Spatial-enabled Analysis featured in the Construction and Energy application domains. It is worth noting that almost all Smart City DT examples featured Spatio-temporal Data Types, with Open Data Sources featuring frequently. In the Manufacturing sample, Location Reference System featured in the top three, whereas Spatial Data Acquisition featured in the Agriculture sample. These results are presented in Table 10. Figure 8 is a bar chart showing the occurrence of all 24 Geospatial DT dimensions across the dataset.

Table 9. Geospatial DT dimensions extracted from dataset.

Geospatial DT Dimensions
Spatio-temporal Data Types
Spatio-temporal Data Formats
Geometric Representation
Locatable Entity/Environment
Geometric Space
Location Reference System
Spatial Data Acquisition
Open Data Sources
Other Data Sources
Positioning System
Spatial Data Storage
Spatial Data Processing
Spatial Data Modeling
Spatial Data Standards
Accuracy of locatable measuring device
Spatial Resolution
Temporal Resolution
Spatial Extent
Temporal Extent
Spatial-enabled Analysis
Spatial-enabled Modeling
Spatial-enabled Visualisation
Spatial Data Sharing
Spatial Transformations

Table 10. Most frequently occurring Geospatial DT dimensions in each application domain.

Application Domain	**Top 3 Geospatial DT Dimensions by Occurrence**
Smart Cities and Urban [32,55,68–91]	Spatio-temporal Data Types (96%) Open Data Sources (58%) Geometric Representation (54%)
Manufacturing and Production [92–104]	Locatable Entity (92%) Spatio-temporal Data Types (85%) Location Reference System (69%)
Construction [105–122]	Locatable Entity (78%) Spatio-temporal Data Types (67%) Analysis (50%)
Energy [123–137]	Locatable Entity (80%) Spatio-temporal Data Types (73%) Analysis (33%)
Agriculture [138–142]	Locatable Entity (80%) Spatio-temporal Data Types (80%) Spatial Data Acquisition (60%)

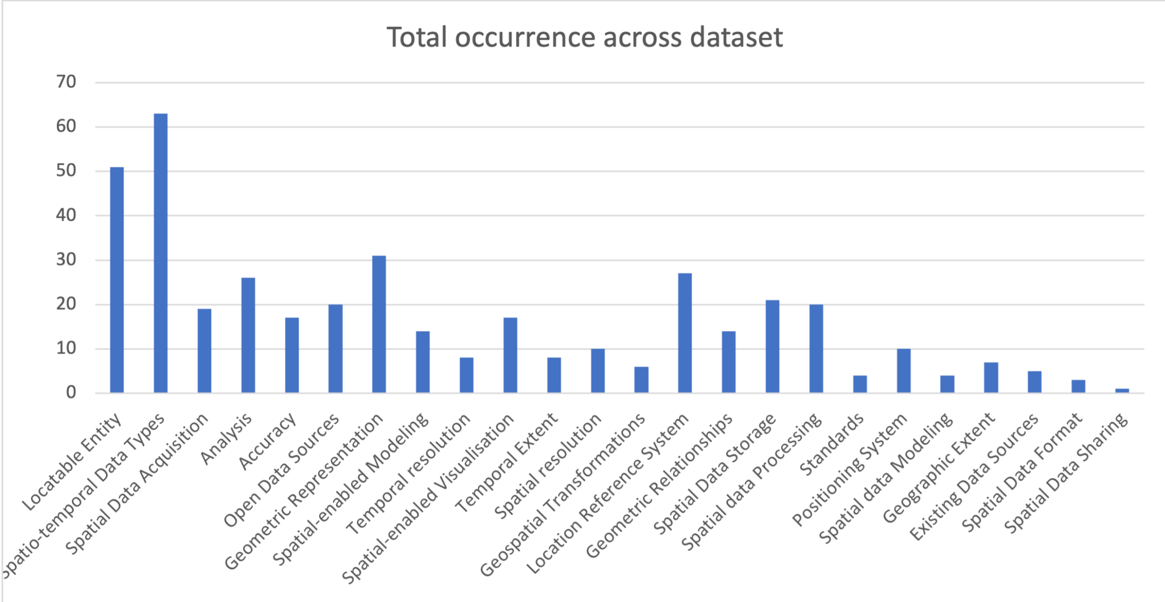

Figure 8. Number of papers that contained each dimension.

Considering the explicit and implicit nature of the papers in the dataset, the 26 explicit papers referenced an average of seven Geospatial DT dimensions per paper, whereas the 51 implicit papers referenced an average of five Geospatial dimensions per paper. This is a difference of two references between the explicit and implicit papers.

On the other hand, considering the Level of Integration of the Geospatial DT examples based on the classification introduced in Kritzinger et al. [47], 29% of the dataset (22 papers) was deemed to be Digital Models, 56% Digital Shadows (43 papers) and 16% Digital Twins (12 papers). The Energy application domain had the highest proportion of Digital Twins, whereas the Smart Cities and Manufacturing application domains had very low proportions of Digital Twins. Nearly half (46%) of the so-called DTs in the Smart City domain were deemed to be Digital Models.

4.4. Step 8: Mapping of Geospatial DT Dimensions

Table 11 highlights the results of mapping existing DT dimensions to the Geospatial DT dimensions identified in this study. There are some clear, direct mappings between the two sets of dimensions. For example, Locatable Entity/Environment maps with the Physical World and associated dimensions in the existing DT space. Moreover, Data Sources in the existing DT space maps with the Geospatial DT dimensions Spatial Data Acquisition, Open Data Sources, Other Existing Data Sources and Positioning System as spatial-specific data sources. Similarly, Spatio-temporal Data Types and Spatio-temporal Data Formats map to Data Categories and Data Formats, respectively, in the existing DT space. The same is true for the Geospatial DT dimensions Spatial-enabled Analysis and Spatial-enabled Modeling mapping directly to the Services DT dimension. Finally, the Geospatial DT dimensions Geometric Space and Geometric Representation directly relate to the existing DT dimension Virtual Representation.

There are, however, some less direct relationships between the two sets of dimensions. For example, the Geospatial DT dimension Temporal Resolution relates somewhat to Twinning Rate but it is not a like-for-like mapping. Geometric Representation, Spatial Resolution and Temporal Resolution relate somewhat to the DT dimension Fidelity but are fundamentally not the same concept. Moreover, the Geospatial DT dimensions Spatial Extent and Temporal Extent loosely relate to the DT dimension Purpose, where the spatial and temporal extent depend on the purpose of the specific DT. The Geospatial DT dimension Spatial Transformations is not considered to relate to any existing DT dimensions.

Table 11. Comparison of existing DT dimensions with Geospatial dimensions identified, where quotation marks (") indicate as stated above.

Meta-Dimension	Dimension	Related Geospatial DT Dimension from This Study
Physical World	Physical Entity [18,20,40,43,46]	Locatable Entity/Environment
	Physical Environment [18,20]	"
	Physical Process [2,18,20]	"
	Physical System [2]	"
Virtual Representation [40]	Virtual Entity [18,43,48]	Geometric Space/Representation
	Virtual Environment [2,18]	"
	Virtual Process [2,18]	"
	Virtual System [2]	"
Connection [43]	Physical-to-Virtual Connection [2,18,43]	**No relatable Geospatial DT dimension**
	Virtual-to-Physical Connection [2,18,43]	"
	Level of Integration [13,20,31,35,46,48]	"
	Twinning Rate [13,18,20,31,35]	"
Data [43]	Formats [36]	Spatio-temporal Data Format
	Categories [36]	Spatio-temporal Data Types
	Sources [19,20,31,36]	Open Data Sources Proprietary Data Sources
	Acquisition [19,44]	Spatial Data acquisition Positioning System
	Governance [19]	**No relatable Geospatial DT dimension**
	No existing DT dimension	Spatial Data Standards Spatial Data Storage Spatial Data Modeling Spatial Data Processing Spatial Transformations
Fidelity [13,18,20,46,48]	Accuracy [35]	Accuracy of measuring device
Services [43]	Analysis [13]	Spatial Analysis Spatial Modelling
	Interface [20,35]	**No relatable Geospatial DT dimension**
	No existing DT dimension	Spatial Visualisation Spatial Data Sharing
Context	Purpose [31,35,46]	Spatial Extent Temporal Extent
	Application Domain [20,46]	**No relatable Geospatial DT dimension**

5. Discussion

The primary goal of this study was to progress the understanding of the role that Geospatial Science plays in application-specific DTs. Making progress on this issue is important so that the Geospatial community can better understand how to engage with DT initiatives that are poised to solve systemic national and global issues, like achieving Net Zero.

This study has made several contributions, including the following:

- A synthesized list of existing DT dimensions;
- A methodology to understand the unstated role of Geospatial Science within DTs;
- A new set of DT dimensions from the Geospatial perspective;

The following subsections address the two research questions and the aim of this study, followed by limitations and future work.

5.1. Implicit Use of Geospatial in DTs

The first research question this study sought to answer was "How explicit is the use of Geospatial in DTs?" The results indicate that there are a considerable number of implicit, unstated uses of Geospatial Science in the application-specific DTs considered. The fact that 51 out of 77 DT case studies reviewed were classified as implicit suggests that more often that not, the use of Geospatial Science in DTs goes unstated. Understanding why this is the case is beyond the scope of this study. In terms of the Geospatial DT dimensions, on average, the explicit DT case studies had seven dimensions, whereas the implicit case studies had five dimensions. This is not a considerable difference, which indicates that the use of Geospatial Science in the implicit DT case studies is broad and encompasses several elements. The results also highlight that Geospatial Science was most commonly associated with the concepts of IoT, BIM and AR/VR. This is perhaps unsurprising, given the Geospatial nature of these concepts; however, this instigates the question of how well understood the role of Geospatial Science in each of these concepts is. In terms of the application domains considered, it is clear that the majority of Smart Cities and Urban DT case studies were classified as explicit, which would be expected, given the development of DTs for entire cities and urban areas and therefore the importance of location [49,53]. However, in all of the other four application domains, the majority of the DT case studies were classified as implicit. The involvement of Geospatial Science in the Construction, Energy and Agriculture application domains is somewhat clear from the spatial extent of these applications; however, the use of Geospatial Science in the Manufacturing application domain is less common, given that the focus is often within buildings and thus not necessarily in geographic space. The results then clearly highlight the opportunity for the Geospatial community to engage more with DTs in the Manufacturing application domain, as well as in those of Construction, Energy and Agriculture, where there may be possibilities to exchange knowledge and improve outcomes.

A particular example in Meža et al. [111] from the Construction application domain highlights how implicit examples use Geospatial Science without being explicit: "sensors that produce outputs of a surface-wise character much like polygons" [111] (p. 6). This statement alludes to a raster representation of Geospatial data, a concept well known in the Geospatial discipline, but does not explicitly state it.

5.2. Geospatial Dimensions of DTs

The second research question this study sought to answer was "What are the Geospatial dimensions of DTs?" The 24 Geospatial DT dimensions defined from the DT case studies provide a comprehensive overview of the Geospatial aspects of DTs. When compared with the elements of a GIS as defined in Duckham et al. [28], we found no gaps in the Geospatial DT dimensions, suggesting the broad role of Geospatial Science in DTs. Concepts specific to Geospatial Science, such as transformations, location reference systems, spatial extent and spatial resolution, were all explicitly or implicitly mentioned in the DT case studies reviewed.

The fact that Spatio-temporal Data Types featured as a top dimension in all five application domains unsurprisingly highlights the widespread use of spatio-temporal data in DTs. Similarly, the Locatable Entity dimension also frequently occurred, driven by the common use of IoT sensors in DTs, as highlighted by the implicit examples discussed in Section 5.1. As measuring devices, sensors are entities that can be located in space and time and therefore constitute a Geospatial dimension of a DT. The representation of the data collected by sensors, temperature, for example, is a spatial representation problem, something that the Geospatial community has experience in addressing. Location Reference System featured in the top three Geospatial DT dimensions in the Manufacturing application domain, as many of the case studies involved indoor localisation. Whilst these are not necessarily "geographically referenced" datasets, they are still problems that involve space and time. In the Smart Cities application domain, Geometric Representation and Open Data Sources both featured in the top three Geospatial DT dimensions. Geometric representation is a key part of smart cities, given the focus on 3DCMs [31]. In addition, open data sources are widely utilised for representing large urban areas, like cities [86].

The Geospatial DT dimensions also highlight limitations with the existing DT dimensions, not least the fact that most of these dimensions have been defined from a manufacturing or engineering perspective. The current DT dimensions do not necessarily capture the importance or intricacies of dealing with Geospatial data. For example, in Liu et al. [134], an implicit DT example in the Energy application domain relating to the operation and maintenance of floating wind turbines involves transformations from a global coordinate system to a local coordinate system by using a coordinate transformation matrix. In existing DT dimensions, there is no provision for capturing spatial transformations and coordinate systems, which are critical to this particular DT delivering value.

5.3. Understanding the role of Geospatial Science in DTs

The results in this study offer some indication of the breadth and depth of the role of Geospatial Science in DTs. In terms of breadth, the number of implicit uses of Geospatial Science highlights that the role of Geospatial Science is possibly larger than stated. In addition, it highlights that there are a large number of DTs that the Geospatial community are possibly not engaging with, thus not contributing their knowledge and experience of the Geospatial discipline. In terms of depth, the 24 Geospatial DT dimensions highlight that a significant number of aspects of Geospatial Science are involved in DTs to varying degrees. These Geospatial dimensions now serve as a basis for understanding the Geospatial aspects of DTs moving forward. They highlight aspects of Geospatial Science that are utilised more than others and how different domains are using Geospatial Science differently.

5.4. Limitations and Bias

Despite this study successfully progressing our understanding of the role of Geospatial Science in DTs, there are several limitations to note.

Firstly, the application domains considered in this study were selected for their relevance to making progress on Net Zero and sustainability both globally and nationally (based on Papadonikolaki et al. [8]). There are other DT application domains, such as Shipping, Mining, Healthcare, Pharmaceutical, Space, Petroleum and Public Sector [8,46], which were not considered in this study. Future work should consider the role of Geospatial Science in these application domains to gain a comprehensive picture of the DT landscape.

Further to this, it should be noted that the Agriculture application domain only contained five papers, indicating a lower volume of Geospatial DT implementations in the agriculture space. This may be due to missing explicit or implicit search terms or the fact that DT implementations in agriculture are less common in the DT literature. Nonetheless, the interpretation of the Agriculture domain results may not be representative and should be used with caution.

Secondly, the explicit and implicit Geospatial search terms used in this study are not exhaustive and do not account for differences between British and American English spelling. It is likely that accounting for this, as well as defining a more extensive set of search terms, would return additional DT case studies beside those considered in this study.

Thirdly, despite case studies being labelled DTs, they refer in fact either to a Digital Shadow or Digital Model based on the classification proposed in Kritzinger et al. [47]. In this study, the results support this, with only 16% of the 77 papers being deemed true DTs. This supports the statement made in Stoter et al. [34] that DTs can be a catch-all term. The classification in Kritzinger et al. [47] is in fact a manufacturing perspective on DTs and alternative classifications should be considered to categorise DTs as they emerge.

Moreover, whilst there has been an exponential increase in the DT literature in recent years, it is still an emerging field, with many DT examples not being in the academic literature despite being active in the world. There are likely further Geospatial DT dimensions in the grey literature.

Bias in this study was minimised through the use of the PRISMA systematic review methodology [59]. Our searches included Geospatial terms, as we sought to identify examples of Geospatial DTs, rather than consider DT case studies independently of Geospatial Science. In light of this, we were careful not to overstate the significance of Geospatial Science to DTs as a whole.

5.5. Further Work

The Geospatial DT dimensions identified in this study have not yet been validated with an additional dataset. This is a priority for further work, in addition to understanding each of the dimensions in more detail, such as the different possible values. These dimensions could then be used to classify Geospatial DTs by using typology or taxonomy as described in Section 2.

There is also the opportunity to utilise these dimensions further and look more closely at the role of Geospatial Science in the entire DT workflow (i.e., from conception to retirement). For example, future work could define the stages of the workflow where Geospatial dimensions occur the most. In addition, the Geospatial dimensions could serve as a basis for considering not just the role of Geospatial Science in DTs but also its importance. Such future work could consider the value of application-specific DTs with and without Geospatial elements and build on existing work on the value of DTs and the value of Geospatial Science.

As noted in Section 3, we seek to further iterate the Geospatial search terms used in this study. We plan to run a survey with members of the Geospatial community to validate these terms and their classification as explicit or implicit. We also plan to account for English language differences between British English and American English. Future versions of these terms could then be used to identify further examples of Geospatial DTs.

In addition, given that DTs are a fast emerging domain, we recognise that many examples have not yet reached the academic literature. Whilst, in this study, we focused almost primarily on the academic literature (both journal and conference proceedings), in future work, we plan to look at the grey literature, including reports, white papers and articles, to ensure that the full DT landscape has been reviewed.

Finally, in the future, we plan to focus on a particular stakeholder group in the Geospatial community, i.e., National Mapping and Cadastral Agencies (NMCAs), to understand their role in DTs and the implications of the dimensions identified in this study.

6. Conclusions

This study considers DTs from a Geospatial perspective and seeks to further the understanding of the role that Geospatial Science plays in DTs. The systematic approach using implicit and explicit Geospatial terms proved a useful way to uncover unstated uses of Geospatial Science in DTs found in the academic literature. Several conclusions can be made from the results of this study. Firstly, a considerable number of implicit uses of Geospatial Science in DTs were identified across the five application domains, suggesting that the use of Geospatial Science in DTs is more widespread than stated in the literature. Secondly, as a result of this, it is possible that there are a significant number of application-specific DTs that are not receiving attention from the Geospatial community. Thirdly, the Geospatial dimensions defined in this study highlight that all aspects of Geospatial Science are present in at least one DT case study and that application-specific DTs utilise different aspects of Geospatial Science. However, when considering a commonly used classification of DTs, a very small proportion of the DT case studies considered were deemed as true DTs, suggesting the need to evaluate other methods of classifying DTs in the Geospatial context. Finally, the methodology and Geospatial DT dimensions defined in this study can be iterated in the future to develop a more complete understanding of the role of Geospatial Science in DTs. With this, expertise and experience from the Geospatial community can be fully utilised, and DTs can address critical global and national systemic issues and ultimately deliver the value they set out to achieve.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DT	Digital Twin
PLM	product lifecycle management
IoT	Internet of Things
NMCA	National Mapping and Cadastral Agency
AR	Augmented Reality
VR	Virtual Reality
BIM	Building Information Modelling
GIS	Geographic Information System
SLR	systematic literature review
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
3DCM	3D City Model
SDI	Spatial Data Infrastructure
CIM	City Information Model
GPS	Global Positioning System
ML	Machine Learning
DL	Deep Learning

Appendix A

Table A1. The 77 papers analysed in this study by application domain.

Application Domain	Sources
Smart Cities and Urban	[32,55,68–91]
Manufacturing, Production and Aerospace	[92–104]
Construction	[105–122]
Energy	[123–137]
Agriculture	[138–142]

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