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RESEARCH ARTICLE

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A taxonomy of built asset information coupling

Abstract The digital transformation of the built asset industry is moving toward closer integration of physical and digital assets and resources. Within the framework of Cyber-Physical Systems (CPSs) and Digital Twins (DTs), an increasing number of studies focus on the technical aspects of CPS and DT. However, a unified framework describing the dimensions and characteristics essential for integrating lifecycle information remains elusive. To leverage these concepts effectively, it is necessary to develop new frameworks to classify and put into relationship various components that comprise the lifecycle information integration of physical and digital assets and resources. This paper addresses these gaps by proposing a taxonomy of Built Asset Lifecycle Information Couples, which outlines the dimensions and characteristics crucial for the lifecycle information integration of built assets and resources. The proposed taxonomy contributes to the efforts aimed at organizing the knowledge domain of lifecycle information management in the built environment.

Keywords asset coupling, taxonomy, digitalization, lifecycle information management, built environment

1 Introduction

The rapid digital transformation of the built asset industry offers opportunities to enhance performance, quality, and value creation by adopting advanced digital technologies and integrated systems. Several successful examples illustrate the potential of combining physical and digital built assets and resources (Maheshwari et al., 2022; Mirarchi et al., 2020; Østerlie and Monteiro, 2020). This integration has been demonstrated through recent research on cyber-physical systems (CPSs) and Digital Twin (DT) applications in the built environment. The use of DTs has yielded promising results, enabling industry professionals to visualize and monitor physical assets at various levels of detail and granularity throughout the asset lifecycle (Camposano et al., 2021). As the focus on digitalization intensifies in the built asset industry, DTs are increasingly recognized for their ability to transform the relationship between the construction process and human behavior (Xue et al., 2010). This shift is driven by the rapid advancement and widespread adoption of technologies that facilitate the integration of physical and digital assets.

Despite receiving significant attention, the concept of DT remains unclear due to the way the term “digital twin” is being promoted and utilized. While several taxonomies have helped to define and describe DT within industry and academia, most of these taxonomies focus solely on its technical features and specific use cases (Niu et al., 2019). This narrow focus often overlooks the broader implications and potential applications of DT, particularly in terms of information flow throughout the lifecycle of an asset. As a relatively new field of study, the industry faces the challenge of establishing a set of characteristics and principles that underscore the importance of lifecycle information coupling.

At its core, asset coupling involves translating changes in one asset (such as a component’s state or location in the physical world) to corresponding changes in another asset (in the virtual world), and vice versa (Succar, 2023). Over the past few decades, numerous research endeavors have sought to develop theories and models for translating between physical and digital assets through various virtual works (Burton-Jones and Grange, 2013). However, inconsistent terminology and characteristics have contributed to confusion surrounding the concept of asset coupling. This confusion is particularly evident at the organizational and management levels, where stakeholders struggle to effectively utilize the coupling of digital and physical assets for asset management purposes (Juarez et al., 2021). As a result, significant information gaps exist between assets, people, machines, and other resources (Lawrenz et al., 2021). Therefore, a common framework is necessary to precisely define elements such

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as states and statuses, purposes, results, types, levels, links, actions, metrics, and enablers that help characterize the concept of asset coupling.

Recognizing the current gaps and challenges present in existing literature, the objective of this paper is twofold. First, it aims to define the main characteristics that support the concept of lifecycle information coupling for built assets and resources in the built asset industry. To achieve this, the work expands on key constructs of the Lifecycle Information Transformation and Exchange (LITE) framework, "An extensible conceptual framework for defining, managing, and integrating project and asset information across its lifecycle [that] provides the foundation for a new information management paradigm, which supports emerging technologies and practices aiming towards integration and automation" (Succar and Poirier, 2020). Secondly, the paper will articulate these characteristics into a new taxonomy specifically designed for lifecycle information coupling of built assets and resources.

The paper begins with an overview of the concept of asset and information coupling, aiming to identify the state-of-the-art and related works. It then emphasizes the need for a taxonomy by providing context and background on the LITE framework. Finally, the paper proposes the Lifecycle Information Coupling taxonomy as the result of this research, establishing a foundation for future studies and implementations in this field of research.

2 Research background

2.1 The concept of asset and information coupling

Main Asset and information coupling involves the process of linking digital assets that accurately correspond to their physical counterparts. This linkage enables changes in one asset, whether in the virtual or physical world, to be translated to its counterpart (Succar, 2023). The term "Asset" refers to either a physical entity (e.g., component or part) or a digital entity (e.g., 3D model), which holds value for an organization (Succar and Poirier, 2020).

The built asset industry uses various levels of asset coupling, ranging from facility and system to component and part (Succar, 2009). During the linking and translating process, the states of asset coupling can be classified as either "tightly coupled" or "decoupled" (Lu et al., 2020). Tight coupling denotes a state in which digital representations heavily rely on physical referents and vice versa (Bailey et al., 2012). In other words, in a tightly coupled state, physical and digital components of an asset are designed to work together, mirroring each other visually and functionally. Any change made to one component necessitates corresponding changes to the other component. On the other hand, loose coupling occurs when a digital asset and its physical counterpart exhibit a lower degree of dependency or correspondence (Østerlie and Monteiro, 2020). Scholars and practitioners across various fields and industries have underscored the need for effective frameworks and models to support the lifecycle information coupling of built assets and resources (Østerlie and Monteiro, 2020). In terms of asset coupling, numerous CPS frameworks and DT models have been introduced. While both concepts originated around the same time, the academic community in Architecture, Engineering, and Construction and Facility Management has proposed various system architectures, use cases, and enablers for CPS. On the other hand, interest in DTs for the built asset industry has only recently emerged. Tao et al. (2018) defined CPS more broadly, stating, "CPS are multidimensional and complex systems that integrate the cyber world and the dynamic physical world." This definition focuses on the integration of computation, communication, and control within physical processes. The DT model presented by Michael Grieves was one of the earliest attempts to conceptualize Digital Twins. It focused on how manufactured products meet their as-planned specifications using DT capabilities in data visualization and exchange (Grieves and Vickers, 2017). The fundamental concept of DT revolves around three components, as illustrated in Fig. 1: physical space, virtual space, and the connection area for data flow and exchange (Boje et al., 2020). The physical space, such as a building, includes elements like sensors and devices responsible for capturing and transmitting data to the virtual space (Zheng et al., 2019). In turn, the virtual space utilizes virtual environment platforms and multiple engineering models to facilitate various virtual operations like control, prediction, or visualization (Juarez et al., 2021). Cloud data storage is often utilized to store meaningful data for efficient accessibility

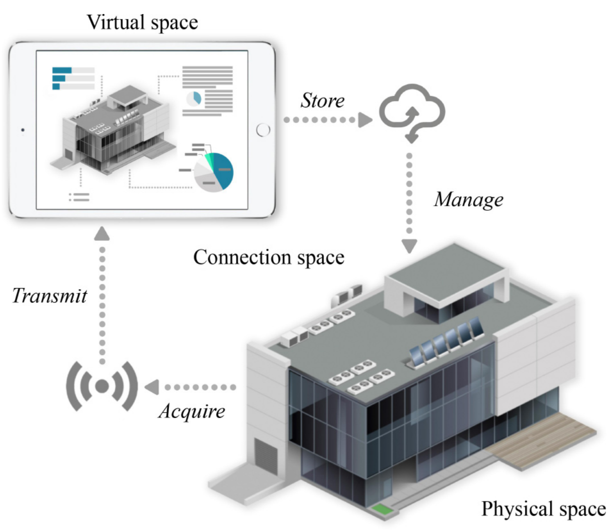

Fig. 1 Basic components of a DT – adapted from Boje et al. (2020).

and management of processed data (Akanmu et al., 2021). The connection space bridging the virtual and physical worlds links the raw or processed data from the physical space to the virtual space and vice versa (Borangiu et al., 2020).

Since Grieves' proposal, an increasing number of studies have focused on the mechanisms and system architectures of "digital twinning." These studies are driven by the emergence of new technologies (El Saddik, 2018). Unlike CPS, DTs utilize a variety of virtual models to represent the past, present, and future states of physical assets. These models incorporate both input data and outputs (Boje et al., 2020).

One crucial feature of DT is its ability to predict the future behavior of physical assets, which is particularly important at the organizational level. This predictive capability relies on the use of reliable and accurate data for effective long-term decision-making (Kuster et al., 2017). When comparing physical and digital built assets, a DT model incorporates multiple quantitative and qualitative characteristics. It also includes tolerance corridors that allow users to identify both positive and negative deviations in processed data (Grieves, 2015).

Data integration is one of the most significant aspects of digital twinning as it enables real-time decision making (Boje et al., 2020). Kritzinger et al. (2018) identified the 'Level of Data Integration' as a dimension to evaluate the extent of integration between physical and digital assets. This integration is categorized into three types: (1) Digital Model (DM), (2) Digital Shadow (DS), and (3) DT. A 'Digital Model' represents a physical referent through a manual, one-directional data flow. On the other hand, a 'Digital Shadow' is characterized by an automatic, one-directional data flow between the physical object and its digital model. Lastly, a 'Digital Twin', as defined by Juarez et al. (2021), is a virtual representation that mirrors the behavior of its physical counterpart through an automatic, bi-directional data flow.

Lu, et al. (2020) have developed a hierarchical architecture for the DT development of buildings and cities. The proposed architecture incorporates key actions to integrate physical and digital built assets, including: (i) data acquisition from the physical space using contactless technologies such as distributed sensor systems, radio-frequency identification (RFID), or image-based techniques; (ii) transmission of data to the virtual space using various communication tools, such as wireless local-area network (WLAN); (iii) integration of acquired data with digital models in the virtual space; and (iv) utilization of coupled physical and digital built assets for various services such as energy management, asset management, security, and health management. Several enabling technologies can facilitate data acquisition, transmission, and integration within built assets. However, challenges arise when extensive data are generated and exchanged across asset lifecycles (Wang et al., 2020). Before integrating information between physical and digital assets and resources, a significant amount of the acquired data may consist of unreliable signals or noise that needs to be filtered. Østerlie and Monteiro (2020) conducted an empirical study on offshore oil production and identified three mechanisms for translating acquired sensor data into operationalizable knowledge: (1) data aggregation, which involves filtering irrelevant data and signals to identify the most reliable and desired sensor data; (2) signal coupling, which connects the digital representation to its physical counterpart; and (3) modeling, which involves creating digital representations to materialize data into knowledge that supports the organization's day-to-day operations.

A comprehensive understanding of the physical world is a fundamental requirement for asset coupling, as physical technologies actively map real entities, processes, and activities into virtual space. Various model engineering (ME) technologies are necessary for modeling digital assets, supporting model construction, VV&A (verification, validation, and accreditation), visualization, and evolution of a model lifecycle (MLC) (Zhang et al., 2021). To establish a connection between digital and physical built assets, the application of Internet of Things (IoT) devices, data communication networks, visual capture (cameras), remote sensors (e.g., satellite imagery for large structures), Application Programming Interfaces (APIs), Web services, and security protocols is essential. However, managing and processing large-scale data efficiently and in real-time can be challenging due to the extensive data generated throughout the lifecycle of built assets (Tao et al., 2018). Therefore, leveraging data technologies is highly recommended to create an accurate and reliable digital representation of a physical entity (Zhang et al., 2022). The output of asset coupling relies on specific software technologies, common data environment (CDE) platforms, service-oriented architecture (SoA), and knowledge technologies to deliver the necessary services.

In addition to the enabling role of these technologies in asset coupling, comprehensive frameworks are required for lifecycle information coupling and integrated management, connecting the design, delivery, and utilization of physical and digital built assets (Succar and Poirier, 2020). As traditional concepts and models are formalized and standardized to enhance data transformation and exchange across various construction sectors, there is a need for more dynamic and modular frameworks focusing on information coupling between physical and digital built assets. Moreover, conventional practices have resulted in fragmented and inflexible formulations for built asset information management, leading to a lack of connectivity between the planning, delivery, and use stages. This limitation restricts users' ability to gain insights and make informed decisions throughout an asset's lifecycle (Alnaggar and Pitt, 2019). The LITE framework (Fig. 2), proposed by Succar and Poirier (Succar and Poirier, 2020), addresses the current challenges in digitalization of lifecycle information management. The LITE framework considers the flow and evolution of information along specific paths and milestones, facilitating the delivery, realization, and subsequent reuse or recycling of assets through closed and open loops.

The framework's modular information components offer flexibility in representing various types, functions, and scales of assets. Specifically, the framework accommodates different levels of granularity in asset scale, ranging from individual functional components (such as a controller box) to portfolios of larger or smaller sub-assets (such as a site or an entire city), ensuring comprehensive coverage. The framework provides distinct conceptual constructs and incorporates them into a comprehensive model. Regardless of their scale, assets are categorized as targeted or actualized. These assets can exist in physical, digital, or both forms, and can be coupled and interact with each other in various ways. The information flow within the LITE framework can be consolidated and merged across eight information milestones. Throughout the information lifecycle, the information can be integrated into a unified pool of overlapping information sets.

Of particular interest in the context of this paper is the significant focus placed on the six information-milestone couples, as highlighted in Fig. 2. Each couple addresses a specific aspect of the information lifecycle, bridging two distinct divides: between the physical and digital worlds, and between the targeted and actual status of assets and resources. The four vertical couples – Purposes Couple, Physical Couple, Digital Couple, and Resources and Method Couple – establish connections between the targeted and actual information statuses. Additionally, to maintain consistent alignment between targeted and actual deliverables, the framework introduces two horizontal couples: Deliverable Couple and Asset Couple. This characterization provides opportunities to enhance information coupling at various stages of the asset lifecycle. While the LITE framework offers a broad overview of information coupling types, it falls short in addressing the nuanced and complex details of their characteristics within the asset lifecycle. The proposed taxonomy aims to provide granular details regarding coupling actions, states, metrics, and enablers, which are essential for practical and technical applications. This granularity is not just an extension but a contribution to meet the complex demands of asset information management, ensuring a more precise, efficient, and tailored approach in information handling and utilization. Consequently, the need for this detailed taxonomy becomes evident, as it fills the critical gaps left by the LITE framework, offering a more detailed and practical guide for stakeholders in managing and optimizing information throughout the lifecycle of assets and resources.

2.2 Related taxonomies of asset and information coupling

Taxonomies, within the context of information systems (ISs), refer to hierarchical classifications or categorization schemes that organize information based on predefined categories (Oberländer et.al, 2019). By classifying objects into specific categories and sub-categories, taxonomies enhance the understanding and analysis of complex domains for researchers and industrial practitioners (Miller and Roth, 1994; Nickerson et al., 2013).

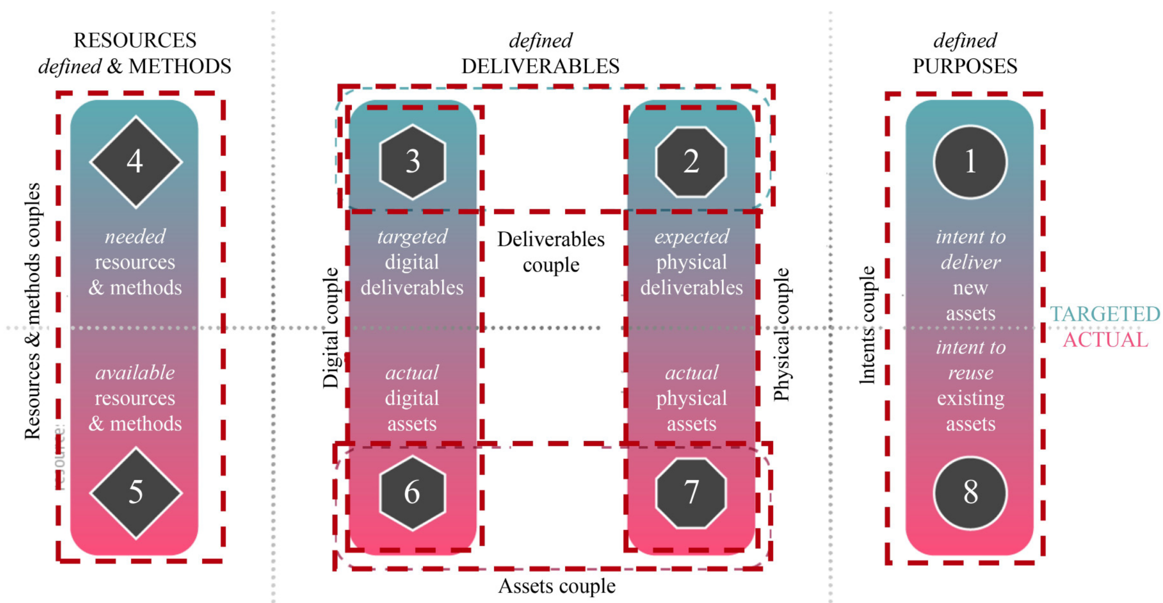

Fig. 2 LITE framework - Information Milestones and their couples – adapted from Succar and Poirier (2020).

The development of domain-specific taxonomies is rapidly advancing, with various examples in the field of asset and information coupling. In response to the growing trend of identifying key features of DTs, Haße et al. (2020) conducted a literature review on DT definitions and proposed a taxonomy (Table 1) that includes eight high-level dimensions for better classification of the most common characteristics of a DT. These dimensions are mutually exclusive and describe the quality aspects of a DT in terms of data link, purpose, interface, synchronization, data input, time of creation, conceptual elements, and accuracy. In this study, the characteristics represent potential modes, types, or aspects of a digital twinning process. A dimension may comprise multiple characteristics. However, the applicability of these characteristics may vary depending on the project's scope and objectives.

A similar approach was adopted by Yaqoob et al. (2020), who developed a taxonomy of DT literature based on key characteristics such as DT levels, applications, purposes, and enabling technologies. The authors of this study highlighted the role of blockchain in DTs to enhance trust, predictability, accuracy, and data integrity within a DT system. Furthermore, the Digital Twin Consortium®, in one of their latest reports, classified the potential capabilities of DTs required to address various use cases in the construction industry (Milligan, 2022). These capabilities were articulated through a DT capability periodic table (CPT) that includes: (i) Data Services; (ii) Integration; (iii) Intelligence; (iv) UX; (v) Management; and (vi) Trustworthiness. Each capability was further decomposed into sub-capabilities to provide more granular characteristics of DT, such as data transformation, simulation, system monitoring, compliance, visualization, and more. Additionally, the author provided stakeholders with a workflow to guide them in identifying the necessary steps for implementing such capabilities in the construction industry.

Although these classifications may not cover all aspects of DTs, they contribute toward providing insights and knowledge of ongoing progress in asset coupling. In addition to the object-oriented perspective, there is an increasing convergence of principles among studies on asset coupling. For example, the primary "purpose" of creating a digital replica of a physical entity and its corresponding "outcome" is frequently mentioned in the literature. Scholars highlight simulation, data analysis and processing, asset monitoring, and automation of physical activities and processes as the most common reasons for coupling physical and digital built assets (Haße et al., 2020; Milligan, 2022; Zhang et al., 2022; Yaqoob et al., 2020). The outcome of these purpose can lead to improvements in the "value" of built assets and resources in terms of quality, performance, resilience, prediction, sustainability, and insight (Camposano et al., 2021; Foidl and Felderer, 2016; Heinrich and Lang, 2019; Zhang et al., 2022; Yaqoob et al., 2020). To assess how a coupling purpose is achieved, a wide range of metrics can be found in the literature for measuring the representational (e.g., DT accuracy, fidelity, transparency) and functional (e.g., DT level, scale, datalink) behaviors of the coupled built assets (Burton-Jones and Grange, 2013; Haße et al., 2020; L. Zhang et al., 2021; Succar and Poirier, 2020). Furthermore, the classification of enabling technologies and their significance is thoroughly discussed in current taxonomies. As new technologies emerge and existing ones evolve, it becomes crucial to capture and disseminate knowledge associated with these advancements (Hu et al., 2021; Niu et al., 2019). Categorizing enabling technologies into a taxonomy facilitates the documentation, storage, and retrieval of information (Qi et al., 2021). This not only allows for better integration and data exchange between current technologies, systems, and software platforms, but also facilitates future projects in leveraging the collective knowledge and experiences of the industry.

Table 1 Taxonomy of digital twin - adapted from Haße et al. (2020)

Dimension	Characteristics
Data Link	Uni-directional, bi-directional
Purpose	Processing, transfer, repository
Conceptual Element	Physically independent, physically bound
Accuracy	Identical, partial
Interface	Machine-to-machine, human-to-machine
Synchronization	With, without
Data Input	Raw data, processed data
Time of creation	Physical first, digital first, simultaneously

2.3 The need for a Taxonomy

While the taxonomies discussed above provide insight into the definitions and characteristics of DTs within the industry and academia, there are still gaps in common approaches to lifecycle information coupling of built assets. The literature review reveals that existing taxonomies have been improvised or created without prior planning or a predetermined structure. This involves tailoring dimensions or characteristics specifically to the immediate needs or requirements of DTs. Of particular importance is the recognition that built asset lifecycle information coupling should not be limited to the "digital twinning" of physical built assets. As depicted in the LITE framework (Fig. 2), a DT can be seen as a reformulation and instantiation of an "Asset Couple" for industrial practices. The other five information couples also warrant focused attention and further investigation. By developing a taxonomy, the key characteristics of asset coupling can be better clarified, including the entire lifecycle from the intent to deliver an asset to its existing situation and future reuse/recycle potential.

The primary objective of this study is to develop a comprehensive taxonomy that guides the creation of information couples in the built asset industry, a domain where systematic classification is notably lacking. This taxonomy aims to bridge the gap between theoretical principles, procedures, and guidelines, such as those outlined by Parmar et al. (2020), and the practical aspects of asset coupling, which involve actions, purposes, outcomes, and other vital elements. For example, while Sacks et al. (2020) provided a valuable data-driven planning and control workflow for the construction of Digital Twins (DTC), their approach primarily focuses on the modeling, building, monitoring, and evaluating phases within the Plan-Do-Check-Act (PDCA) cycle. This leaves a crucial question unanswered: How does asset coupling effectively translate from the targeted to the actual status of lifecycle information? By developing a taxonomy, this study aims to clearly define the necessary steps and processes for constructing information couples. This will not only provide a structured approach to understanding and applying the principles and guidelines in a practical setting but also ensure that the resulting framework comprehensively addresses the dynamic and multifaceted nature of information management across various lifecycle stages in the built asset industry.

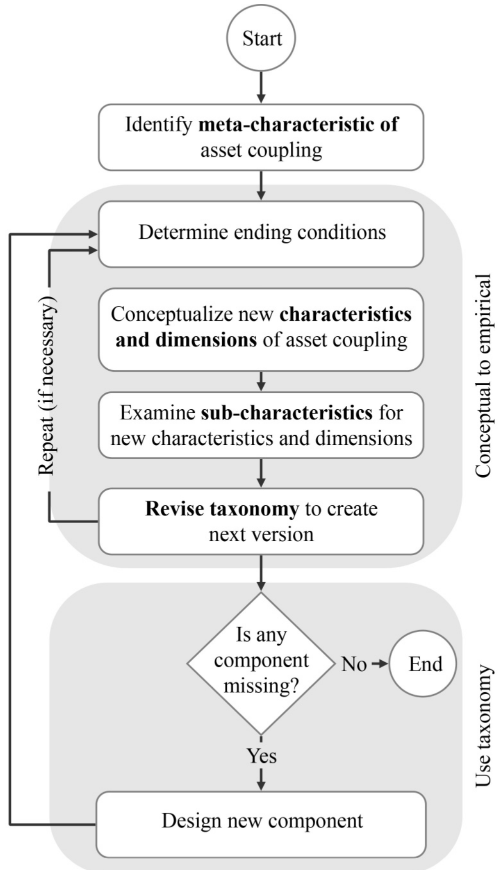

Fig. 3 Taxonomy development method - adapted from Nickerson et al. (2013).

3 Materials and methods

3.1 Taxonomy development method

Creating a taxonomy is a complex task that involves the systematic classification of meaningful data, documents, and models (March and Smith, 1995). According to Bailey (1994), taxonomies are derived either conceptually or empirically. In the conceptual approach, researchers may propose a typology of categories based on theoretical foundations or ideas. Alternatively, researchers can take an empirical approach, which is based on constructed typologies and empirical cases. In either case, a useful taxonomy should have some fundamental attributes, such as being concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013).

Within the context of this research, the concept of lifecycle information coupling of built assets and resources is still in its early stages, and there are only a few theoretical frameworks and models that can support the development of a taxonomy. Hence, the existing coupling characteristics can be conceptually classified into a taxonomy to be used as a research construct for future applications.

To do so, this study adopts the taxonomy development method proposed by Nickerson et al. (2013), which involves a systematic approach to establishing dimensions and characteristics in alignment with the taxonomy's purpose (Fig. 3). This method was specifically chosen due to its robust framework, which is effective in areas with emerging theoretical foundations, such as built asset lifecycle information coupling. Despite the limited empirical data and infancy of theoretical foundations in this domain, the flexibility and structured approach of Nickerson et al. (2013)'s methodology allows for a comprehensive and adaptable taxonomy construction. Nickerson et al. (2013) identified a taxonomy's purpose as a "meta-characteristic." In the scope of this paper, the meta-characteristic is conceptualizing the key dimensions and characteristics of built asset lifecycle information coupling to be expanded and implemented in both academia and industry.

Due to the scarcity and limited availability of data regarding built asset information coupling, this research employs a "conceptual-to-empirical" methodology. This methodology involves conceptualizing the taxonomy's dimensions based on the gathered data and domain knowledge. Each dimension includes characteristics that require examination after the conceptualization step. Once the overall layout of the taxonomy is created, ongoing assessments are conducted to determine if any dimensions need to be revised, removed, or added. As research is continuously evolving, these assessments present opportunities to keep the taxonomy updated in the event of changes.

To assess the effectiveness of the designed taxonomy in fulfilling its primary purpose (meta-characteristic) and to determine when to conclude the method, Nickerson et al. (2013) introduced a set of 13 "Ending Conditions." These conditions include both objective and subjective criteria, enabling researchers to evaluate the utility of a taxonomy. A thorough evaluation of the taxonomy based on these ending conditions should be conducted repeatedly until all the ending conditions are fulfilled. In the development of the proposed taxonomy, a combination of objective and subjective criteria was employed as ending conditions. These criteria included "uniqueness", ensuring that each dimension and characteristic in the taxonomy was distinct; "repetition", to confirm the absence of redundant dimensions and characteristics; and subjective conditions such as "conciseness", which ensured clarity and simplicity in the taxonomy; "robustness", guaranteeing its resilience and relevance across various contexts; and "extendibility", enabling future expansion and adaptation. The application of these ending conditions was an iterative and continuous process, carried out until all the criteria were satisfactorily met. This approach ensured the usefulness and comprehensiveness of the taxonomy.

3.2 Conceptualization of dimensions and characteristics

After delineating the meta-characteristic of the taxonomy, the initial step involves conceptualizing meaningful dimensions and their corresponding attributes. This process entailed gathering a comprehensive array of scholarly publications, industrial reports, thesis projects, and non-textual materials (e.g., drawings, photographs, videos), which were then imported and centralized within a database. Inclusion criteria for data selection were multifaceted, focusing on various key aspects: relevance to the research topic and objectives, impact factor of publications, citation index of documents, expertise and recognition of authors in the field, and diversity of represented disciplines. Conversely, specific exclusion criteria were applied: documents containing outdated or superseded information, publications lacking peer review, and sources from non-credible or non-academic platforms were systematically excluded. Textual documents were sourced from digital databases with extensive resources, such as Scopus, Engineering Village, Google Scholar, and Elicit.

Following the document collection phase, an open coding and classification framework was developed using NVivo software to filter and extract themes from relevant literature. Initially, 160 academic publications and industrial reports across various disciplines (e.g., digital representation theories, lifecycle information management, information and communication technologies, construction and civil engineering) were highlighted for initial coding. Due to the significant volume of coded data encompassing diverse themes and concepts, a hierarchical approach was employed, establishing "Parent Codes" and "Child Codes." Parent codes represent overarching themes or concepts, while child codes encapsulate more specific aspects such as definitions, applications, capabilities, and components. It is imperative to consistently update and revise these child codes in line with new findings (Lee and Fielding, 1996).

The hierarchical coding of literature was followed by coding queries and cross-code analysis within NVivo (Fig. 4). Word or phrase queries were utilized to explore the occurrence and frequency of words within the database. As suggested by Edwards-Jones (2014), any results obtained from research queries should be scrutinized using the following simple questions:

- Is it true for everything/everyone?
- Does it depend on some other variables?

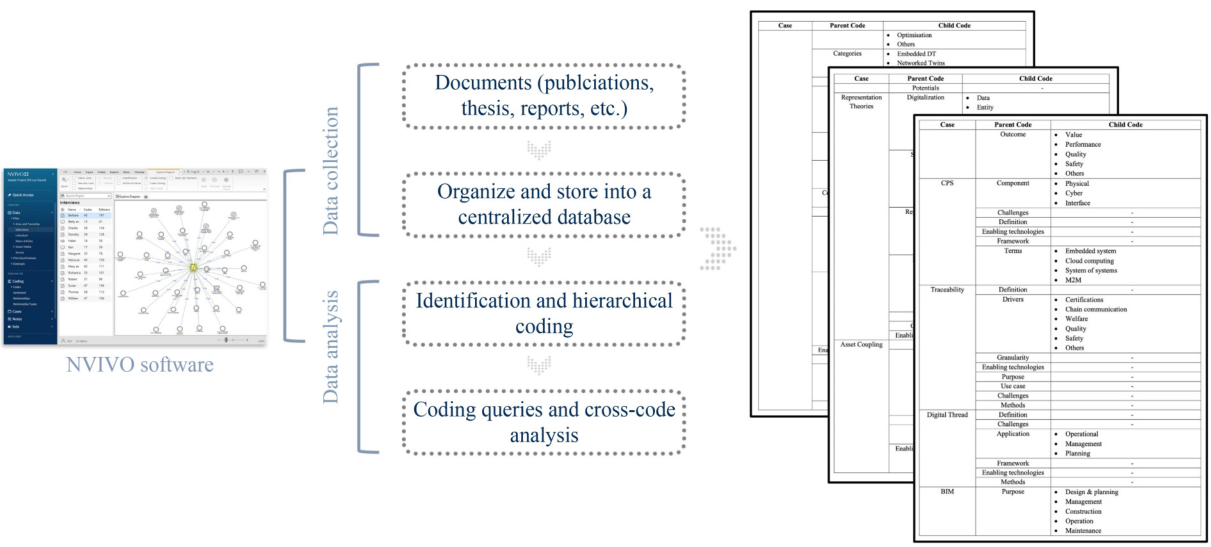

Fig. 4 Overview of the qualitative data analysis conducted in the research.

To enhance the examination of such inquiries and to determine the interconnectedness of codes, a cross-code analysis was conducted, resulting in a comprehensive interpretation of the coded data obtained from the literature. Cross-code analysis, typically utilized in qualitative research, is a method employed to explore and decipher the associations between various themes, concepts, or categories that emerge from a data set. This methodology enables researchers to pinpoint overlapping areas and connections within the coded elements, thereby facilitating a deeper comprehension of the underlying patterns exhibited in the data (Woods et al., 2016). The identification of these overlaps facilitated the data analysis process by highlighting relationships, such as similarities, differences, and potentials, among the coded elements within a single document. A thorough examination of the patterns and interrelationships within the coded literature resulted in the compilation and finalization of all pertinent codes.

Throughout the process of coding the existing literature, a deliberate evolution was observed over a span of 16 months. The transition from coding to establishing the key dimensions of the taxonomy was considered a significant milestone. The comparative analysis yielded a set of dimensions that effectively included various aspects of asset coupling. Subsequently, once the specific characteristics of coupling were identified, a manual grouping and classification process was employed. The resulting groups formed the initial dimensions, which are both mutually exclusive and collectively exhaustive. These dimensions were determined based on factors such as interrelationships (e.g., cause and effect), clarity, comprehensiveness, inclusiveness, and the frequency of findings. This research proposes a concise yet easily understandable set of dimensions and characteristics, which can be further expanded upon in future studies. To shed additional light on these dimensions and their associated characteristics, a detailed explanation will be presented in the subsequent section. The objective of this exposition is to provide a comprehensive understanding that facilitates the effective utilization of the taxonomy as a valuable tool for the implementation of lifecycle information coupling of built assets and resources.

4 A taxonomy for built asset lifecycle information coupling

Figures 5 and 6 illustrate the primary components of the Built Asset Lifecycle Information Couples, representing dimensions in black boxes, characteristics in green boxes, and sub-characteristics in white boxes. These figures represent two levels of the proposed taxonomy. Level 1 provides a foundational context, introducing essential dimensions to ensure a comprehensive understanding of asset coupling. This level includes: Information Couples, Coupling States, Coupling Impacts, Coupling Purposes, Coupling Outcomes, Coupling Actions, and Coupling

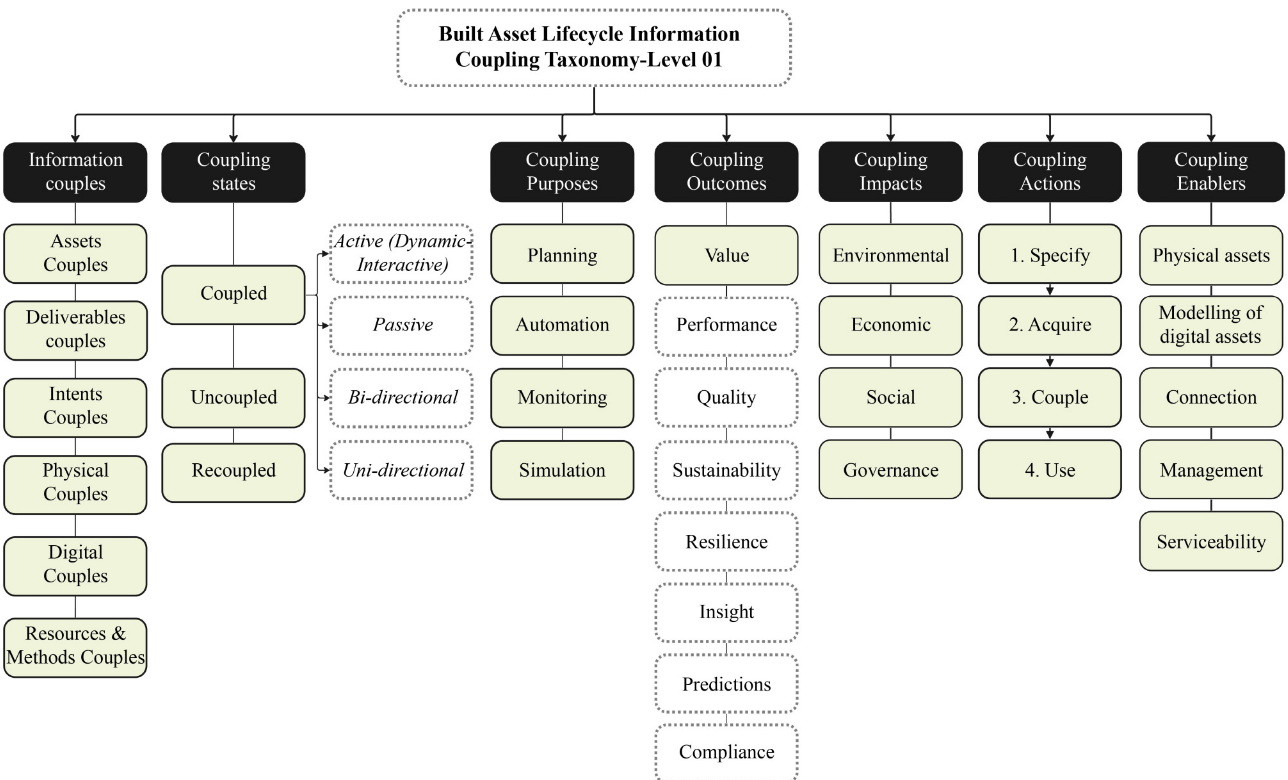

Fig. 5 Built asset lifecycle information coupling taxonomy—Level 1.

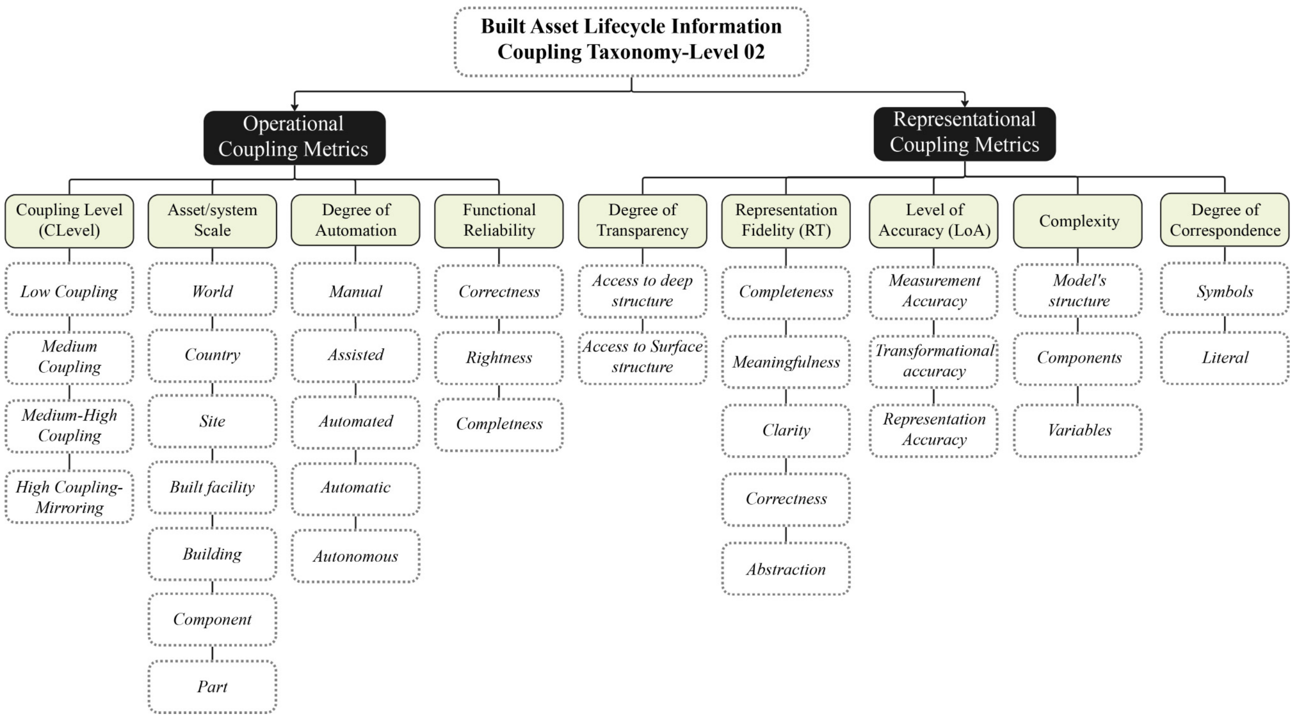

Fig. 6 Built asset lifecycle information coupling taxonomy—Level 2.

Enablers. Level 2 focuses on the potential coupling metrics, ensuring that users can analyze, evaluate, and optimize the asset coupling in a detailed manner.

4.1 Information couples

The first dimension is Information Couples, which includes six coupling types and their role and significance across lifecycle stages of assets and resources. As shown in Fig. 2, Information Couples can be categorized as either vertical couples or horizontal couples. Vertical couples can be used to validate or verify an asset's current state against its targeted state, and they include four types of couples: Intents Couples, Physical Couples, Digital Couples, and Resources and Methods Couples.

Intents Couple plays a crucial role in the exchange of information between two important milestones in the LITE framework: (i) the intention to deliver new assets; and (ii) the intention to reuse existing assets. To effectively deliver a new asset, it is essential to have access to all relevant historical information regarding the project's context and previous practices. This information aids in making informed decisions, preventing construction errors, and reducing costs and time (Brandín and Abrishami, 2021). However, when it comes to recovering or demolishing existing assets, there is often a challenge in recalling all the inter-connected information, especially when multiple parties are involved in the project (Pinheiro, 2004). Therefore, the utilization of Intents Couple becomes an integral part of managing lifecycle information. It enables stakeholders to evaluate whether existing assets are suitable for predefined purposes and determine their potential for recovery and reuse.

As projects progress, commissioning the physical and digital built assets can become increasingly difficult or even impossible due to the absence or abundance of predefined attributes within the deliverables (Çimen, 2021). Zhang et al. (2021) suggest that this concern can be addressed through comparative and integrated approaches, which verify the alignment between de-fined deliverables and the actual assets that are built. The coupling of physical and digital deliverables with their as-built counterparts allows users to access information regarding the specified attributes of the assets.

Given the tangible nature of physical assets, the connection between expected physical deliverables and actual physical assets can be facilitated through direct observation, continuous measurement, and monitoring of physical attributes (Boje et al., 2020). For digital built assets, the utilization of Digital Couple enables users to manipulate and verify the actual data contained within digital deliverables, such as models, documents, and data. For instance, the efficiency of clash detection in digital models can be enhanced through strategic methods. One such method involves actively coordinating and coupling defined digital deliverables, such as 3D geometry param-eters or semantics in IFCs (Industry Foundation Classes) files, with the digital model in the CDE. Although this coupling does not directly reduce the time required for clash detection by software, it optimizes the process by ensuring that the most relevant and up-to-date information is readily available. Consequently, it reduces the need for redundant analyses caused by outdated or incomplete data and streamlines the workflow. This can ultimately result in more efficient utilization of software and computational resources, indirectly leading to a reduction in the overall time spent on clash detection, particularly in complex projects where large volumes of data and frequent updates can significantly impact the detection process.

Another critical concern is the effective management of construction resources, including financial, technical, and human resources, among others. To avoid shortages in any resource type, it is crucial to employ innovative methods and mechanisms (Heinrich and Lang, 2019). An information coupling approach that links “needed resources and methods” with “available resources and methods” can provide valuable insights for resource management and optimization at any scale. In practical terms, selecting resources requires real-time information on their availability, location, impacts, costs, and other relevant factors (Karlsen et al., 2013). However, this information is subject to constant changes, making it difficult to track without coupling it with available resources and methods (Katenbayeva et al., 2016). Therefore, the Resources and Methods Couple is significant, especially when quantifying resource inputs and outputs and assessing resource impacts throughout the lifecycle stages of both physical and digital assets (Upstill-Goddard et al., 2015).

There are two types of horizontal couples: Deliverables Couple and Assets Couple. These couples represent, enable, and measure the synchronization between targeted digital and physical deliverables, as well as actual digital and physical assets commonly referred to as DTs. Prior to delivering any physical and digital assets, the coordination and integration of physical and digital deliverables are often overlooked due to data heterogeneity (Lu, et al., 2020), changes in project strategies (Jenkin and Chan, 2010), or uncertainties in design parameters (Singh and Willcox, 2018). Insufficient alignment between the expected physical deliverables and the targeted digital deliverables can result in misinterpretation of project objectives (Lu, et al., 2020) and the inability to deliver the actual physical and digital assets with the desired level of completeness, accuracy, and reliability (Zhang et al., 2021). The Deliverables Couple offers planners and designers the opportunity to thoroughly review the targeted/expected attributes and variables of an asset early in its lifecycle, helping to minimize potential errors or failures during the delivery of the actual physical and digital assets.

Similar alignment and synchronization can be supported by Assets Couple at actual status of built assets. The concept of Asset Couples, as introduced in the LITE framework, goes beyond the established concept of DT, serving as a comprehensive term that encompasses a broader range of interactions and functionalities within the context of built assets. DT can be seen as a specific embodiment of Asset Couples, emphasizing the continuous, dynamic simulation, optimization, and analytical processes that are crucial for decision-making and performance enhancement of these assets. It is important to recognize that these functionalities are part of the broader concept of Asset Couples.

The terminology of an Asset Couple emphasizes the significance of “actual” physical and digital built assets, which are achieved through the successful delivery of models, documents, and data sets, and are coupled and utilized until disposal. To facilitate the translation of changes from one asset to another, it is crucial to establish a tight coupling between the components or parts of both the physical and digital built assets. Asset Couples utilize digital models, documents, and data sets that accurately represent the behavior of a physical asset throughout its lifecycle stages, including spatial/geometric characteristics, resolutions, colors, textures, etc. (Stojanovic, 2021).

4.2 Coupling states

Coupling states indicates the condition of Information Couples across lifecycle stages (Fig. 7). Three main states can be observed during a coupling process: (a) Coupled; (b) Uncoupled; and (c) Recoupled.

The “Coupled” state refers to a condition in which physical and digital assets and resources are highly dependent on each other, and any changes in one entity directly impact the other. Two types of coupling may occur: (i) Active and (ii) Passive. Active coupling is the preferred state when a system actively generates or transfers a large amount of dynamic data without pause, diversion, or slack. For example, dynamic scheduling is a common method for managing construction resources, involving real-time adaptation of the project schedule as the project progresses (You and Feng, 2020). Unlike active couples, “Passive” couples remain inert until a designated trigger prompts them to act. This trigger could be a direct exertion by an authorized user, input from an external source, or a specific condition that needs to be met (Al-Azri, 2020). Keeping information couples in a passive state is desirable when no real-time interaction is required between assets and resources (Costin et al., 2014). The flow of information in coupled states can occur in two ways: bi-directionally or uni-directionally (Haße et al., 2020). Uni-directional states involve the one-way transfer of information from one entity to another, such as from physical assets to their digital counterparts. In contrast, bi-directional states allow for two-way information flow between different components or parts of the built assets, enabling communication and interaction in a more dynamic and interconnected manner (Madubuike et al., 2022). The term “Uncoupled” refers to the absence of a connection between physical and digital assets. An uncoupled asset does not reflect or correspond to its

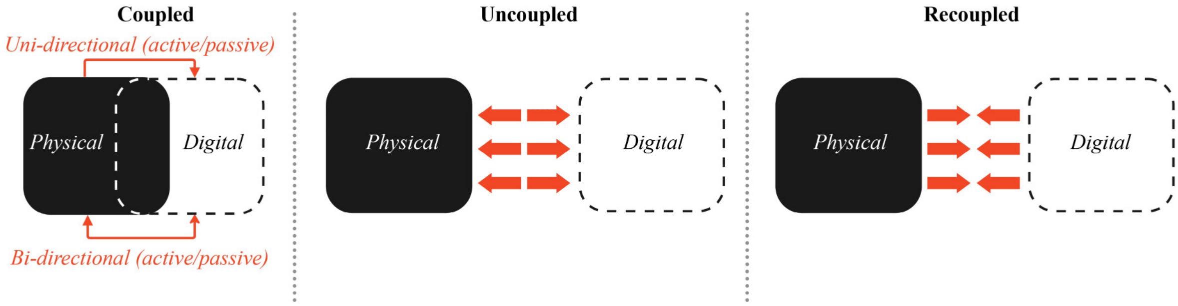

Fig. 7 Overview of coupling states.

counterpart (Østerlie and Monteiro, 2020). The level of correspondence between information couples is minimal in this state, and changes in one asset, such as alterations to the physical properties of a component in real space, are not easily translated to the uncoupled asset. The situation becomes even more complex when multi-disciplinary project teams generate diverse pieces of information that need to be linked and integrated for more effective management of targeted/actual assets throughout their lifecycle (Papadonikolaki, 2018).

To transition from an uncoupled state to a coupled state, it is essential to identify and address the coupling issues between assets and resources, without assuming any interdependencies. Furthermore, users should be given adequate time to find feasible solutions that effectively resolve these coupling issues (Xiao et al., 2012). This process can be carried out during the 'Recoupling' state, which occurs when there is a need to rebuild coordination and connectedness between built assets and resources (Zhou et al., 2022). During the state of recoupling, both the previously uncoupled information and new information can be rearranged and reorganized in preparation for the creation of a new coupled configuration (Covanich et al., 2008).

4.3 Coupling purpose

Coupling purposes refer to the reasons that drive the development and implementation of information coupling in the lifecycle of built assets. Information coupling can support various purposes, including planning, analysis, simulations, automation, and monitoring. The degree of support provided by coupling may vary across these purposes. Although the list of coupling purposes can be expanded in different contexts, the current taxonomy defines high-level purposes based on the diverse information needs in the built asset industry.

• Planning: The initial phase of any project involves defining and articulating the project plan, as well as evaluating the feasibility of the proposed strategies (Umeda et al., 2012). Knowing where to obtain information and how to effectively utilize and interpret it remains a challenging aspect of the planning process (Stein and Moser, 2014). Additionally, planners may seek similar practices in order to learn from them and apply them to new planning activities. Through Information Couples, one can easily identify and reuse valuable information related to current and past conditions of similar practices, thereby avoiding duplication of work. After gathering and interpreting historical information for planning purposes, additional considerations such as available resources, methods, defined requirements, existing regulations, and milestones to achieve within a specific timeframe can be coupled with each activity or process outlined by lifecycle planners.

• Automation: To further increase the performance and efficiency of the built asset, automation is becoming an important factor in implementing Information Couples across lifecycle stages. Any automated system requires continuous optimization and control to deliver the desired value (Elattar, 2008). Information Couples enable users to see which automations are effective and which redundant automations should be retired to mitigate energy waste and reduce operating costs (blueprint, 2022). When automations evolve, the coupled information provides users with a wealth of invaluable insight about the complexity of an automated process, the applications, visibility of performance, maintenance requirements, and more.

• Monitoring: Another common purpose of coupling is the monitoring of built assets using advanced hardware, network, and software solutions. Despite the progress made in technological tools (e.g., IoT devices, RFID tags) for asset monitoring, a number of challenges remain to be addressed. These include the need to ensure adequate visibility of assets (Yaqoob et al., 2020), tracing multiple physical and digital components or parts (Kim, 2020), comprehending the exact issues that must be addressed during the monitoring process (Zhu et al., 2017), and identifying anomalies resulting from the complex nature of integrated systems and the complexity of components involved (Lu, et al., 2020). Information Couples are envisioned to enable alignment between different components of a monitored physical asset. This leads to data transparency (Camposano et al., 2021), real-time visualization of monitored data (e.g., graphs, simulations, tables), easy accessibility to monitored data, and immediate warnings to workers in situations of risk or danger (Boje et al., 2020).

• Simulation: Based on the project objectives, it may be necessary to create model-based simulations as digital deliverables from the beginning or make adjustments to existing simulations. In either scenario, the coupling of targeted and actual assets can save time and effort during model development (Chen and Huang, 2020). Information coupling has significant potential in handling both continuous and discrete event simulations with regard to time (Van der Valk et al., 2020). Model-based simulations are constantly evolving, and well-defined information coupling enables users to gather, process, reuse, and maintain model inputs and outputs at different stages of information progression.

4.4 Coupling outcomes

Coupling outcomes refer to the expected results or consequences of coupling actions under certain conditions. These outcomes can include, but are not limited to, value generation through quality improvement, gaining insights, enhancing sustainability, bolstering resilience, improving performance, making predictions, and ensuring compliance for built assets or resources. The overarching value may change over time in accordance with shifts in project objectives or attributes (CDBB, 2020). However, Information Couples can derive value not only from the coupling of as-targeted and as-built assets but also from innovative ways of recovering and reusing coupled information for future implementations (Camposano et al., 2021). Value can be achieved through the following characteristics:

• Insight: Having access to coupled information at various stages of an asset enables stakeholders to retrieve necessary data and gain insights into concealed relationships or patterns within raw data (Ali, 2020). These identified patterns can serve as a basis for informed decision-making and the execution of strategic actions by stakeholders (Pang et al., 2021).

• Performance: It reflects how well an investment or a portfolio of assets (e.g., machines, equipment, infrastructure, or any tangible or intangible item of value) has performed over a specific period of time (Maheshwari et al., 2022). Information Couples can improve the performance of assets through various methods such as predictive analysis, optimization of “what-if” scenarios, proactive risk management, performance benchmarking, performance reporting and visualization, etc. (Lu et al., 2019).

• Quality: Asset quality refers to how well an asset meets customer needs, fulfills its intended purpose, and adheres to industry standards (Jraisat et al., 2016). Stakeholders can benefit from using Information Couples, which function as a “smart activity tracker” that monitors quality testing, assessment steps, and delivery notes. By examining the coupled parameters and attributes of physical and digital built assets (Foidl and Felderer, 2016), feedback and complaints regarding asset quality can be addressed in a more detailed and efficient manner. Information Couples enable a comparison between the requirements of “quality pre-sets” and the current condition of physical assets, assisting suppliers in identifying quality issues before delivering assets to users.

• Predictions: Predicting future states of assets and resources relies heavily on measured data inputs and outputs, as well as the initial coupling of asset deliverables (Boje et al., 2020). Information Couples serve as an ideal tool for reconciling dispersed data at Information Milestones and optimizing them through the incorporation of simulation models or machine learning capabilities (Brockhoff et al., 2021).

• Sustainability: To achieve genuine sustainable outcomes, integrating cutting-edge technologies and lifecycle information pertaining to assets and resources can assist stakeholders in implementing sustainable solutions throughout all development phases. Successful implementation of sustainable methods and indicators within Information Mile-stones requires access to coupled information that includes environmental, social, and economic aspects of the project (Heinrich and Lang, 2019).

• Resilience: The resilience of the built asset industry in the face of natural, financial, and social disasters or hazards is increasingly important (Sertyesilisik, 2017). The recovery of built assets during the post-disaster phase relies heavily on historical data, which is crucial for integrating past knowledge with innovative strategies. Given the complexities and uncertainties in reconstruction processes, including disagreements among parties (Wang et al., 2015), it is essential to integrate all relevant data on codes, policies, safety measures, along with designs, methods, and resources using Information Couples. Additionally, model-based simulations can be combined with physical built assets to visualize potential risks to the built environment and human health.

• Compliance: The requirement for evidence of compliance is common in the built asset industry in order to verify the completion of specific tasks and demonstrate their effective execution. However, this approach is often slow and may lack accuracy. By utilizing Information Couples, which have a defined purpose of coupling information related to the initial stages of a built asset, it becomes possible to determine whether an executed asset or process has met its primary requirements or if further adjustments are necessary (Ramesh and Jarke, 2001).

4.5 Coupling impacts

The impacts of coupling assets refer to the significant changes in major environmental, economic, social, and governance issues within the built environment (Lv et al., 2022). To optimize these impacts, stakeholders must carefully weigh the benefits of asset coupling against potential complexities. This involves considering the specific requirements of the system or organization, the nature of the assets involved, and the potential risks and benefits of each approach. The impact of asset coupling can be understood through the lens of the Sustainable Development Goals (SDGs), which define the necessary bottom lines for financial growth, social wellbeing, preservation of natural resources, and successful project governance (Hubbard, 2009; Wieser et al., 2019).

From an economic perspective, the profitability of constructed assets depends on stakeholders' ability to undertake larger projects within reduced construction timelines and costs, while enhancing client satisfaction (Jahan et al., 2022). To achieve this goal, coupling projected costs with actual costs (ACs) proves to be an effective approach in enhancing the profitability of constructed assets (Farnsworth et al., 2015). This can be achieved by optimizing the current cost structure of assets and recognizing their potential future value. Another crucial aspect that contributes to economic growth is the effective utilization of recovered built assets. Information Couples enable users to actively gather and record the financial values of both as-targeted or as-built assets. Over time, such data enables stakeholders to make more informed decisions regarding opportunities in secondary markets, the generation of value from discarded materials, and the creation of value from reused assets (Kim et al., 2021). Despite these positive impacts, asset coupling incurs high initial costs and risks of financial misestimations due to complex data integration. While Information Couples facilitate decision-making, these systems must also navigate the financial uncertainties and potential delays in project timelines.

The comprehensive understanding and effective utilization of natural resources are pivotal considerations in the built asset industry (Singh et al., 2011). To facilitate the transition toward a circular economy, it is crucial for stakeholders to possess detailed information regarding material usage, energy consumption, land utilization, waste generation, and emissions throughout an asset's lifecycle. This data can be optimized during the design and construction phases by incorporating relevant environmental certifications and policies, thereby ensuring transparency and minimizing any uncertainty regarding the long-term environmental impacts of the assets and resources used. During the operation and maintenance (O&M) phase, the negative environmental effects of built assets can be rapidly identified and mitigated by coupling information on their materials (e.g., biological, chemical, and physical properties), products, and waste generation (Heinrich and Lang, 2019). However, the advantages of this approach can be counteracted by the increased energy demands of systems and the challenges associated with accurately tracking and managing environmental data.

While studies on the environmental and economic lifecycle assessment of assets are abundant, there has been a relative scarcity of research on the social impacts of built assets in the industry (Çimen, 2021). Analyzing the influence of coupled information on social sustainability involves four primary categories (Labuschagne and Brent, 2008): (i) internal human resources, which include employment opportunities, labor sources, and career development; (ii) external population, comprising factors such as health, education, and housing; (iii) macro social performance, which encompasses economic welfare and trading opportunities; and (iv) stakeholder participation, including elements like stakeholder influence and information provision. Each of these categories can be analyzed using specific sets of information ranging from the planning stage to the O&M of built assets. Nonetheless, there are drawbacks to consider, including potential job losses due to automation and concerns regarding privacy stemming from the extensive collection of social data. These factors can significantly impact public trust and willingness to engage with built asset projects.

To ensure the ethical and logical decision-making process in order to achieve the SDGs, the importance of effective organizational and project governance is increasing (Müller et al., 2014). Asset coupling is a method that simplifies the reporting process by integrating project data and aligning it with organizational information needs. While many organizations protect their data due to commercial competition or security concerns, Information Couples can add value by focusing on the insights derived from data rather than just the data itself (Østerlie and Monteiro, 2020). This shift in perspective encourages organizations to prioritize meaningful results from data analysis rather than solely valuing raw data. However, it is important to acknowledge the risks associated with relying on data, such as issues of data accuracy, integrity, and the potential for overlooking non-quantifiable factors in decision-making. Therefore, a robust governance framework should include effective data management strategies and a critical evaluation of data-driven decisions to mitigate these risks and ensure balanced and ethical governance.

4.6 Coupling actions

Coupling actions refer to the processes and activities involved in establishing and maintaining lifecycle Information Couples. After defining the purpose of coupling, coupling actions proceed through four steps (Fig. 8): (1) Specification; (2) Acquisition; (3) Coupling; and (4) Utilization.

As illustrated in Fig. 8, coupling actions are divided into two information statuses: "as-targeted," which represents the information that needs to be specified and acquired, and "as-built," which indicates information that is already coupled and ready for use. Targeted information is specifically identified and acquired to facilitate information transmission for coupling actions, while as-built

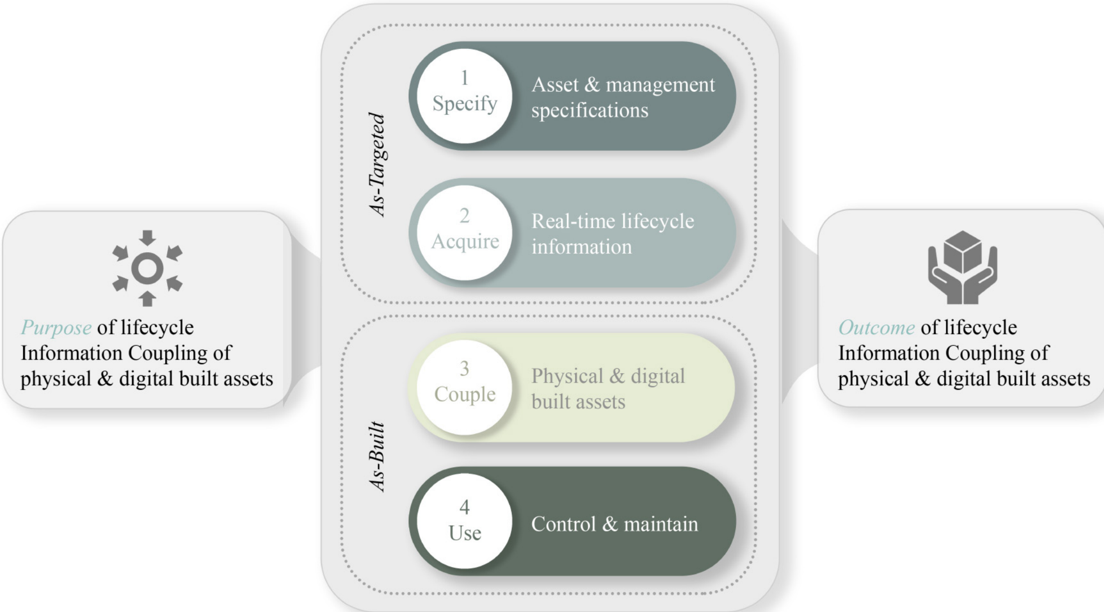

Fig. 8 Coupling actions.

information exists within the coupled digital and physical built assets and resources. It is important to note that both targeted and as-built information can be identified in either physical form within the built environment or in digital information containers such as models, documents, and data.

4.6.1 Specify

Once the purpose of coupling is determined, the initial step involves specifying the data required for coupling built asset lifecycle information. All specifications should cover pre-existing data (e.g., digital documents of a physical asset that have already been created) as well as data that does not yet exist (e.g., project schedules or design models that need to be created). In either case, stakeholders (e.g., project owners, managers, or regulatory bodies) should carefully outline the necessary specifications for the targeted asset or project by engaging in a series of meetings (Zegarra and Alarcón, 2019). A successful specification of targeted data relies on a thorough investigation of heterogeneous databases across disciplines. This involves mapping and aligning databases, resolving interoperability issues, and managing varying metrics and codes (Yang and Zhang, 2006). The complexity of this step should not be underestimated, as it requires collaboration and coordination between different teams, each with their own data systems and formats.

4.6.2 Acquire

Data acquisition involves gathering and collecting data from a variety of sources, including existing physical and digital built assets (Pang et al., 2021). The methods of data acquisition can vary depending on the nature of the assets and the specific project requirements (Haße et al., 2020). Manual data acquisition involves the direct and hands-on collection of information by individuals, which can be time-consuming but offers a high level of control and precision. On the other hand, automated data acquisition utilizes technology and sensors to retrieve data automatically in real-time, ensuring efficiency and scalability for large-scale projects. While automated data acquisition offers significant benefits, manual methods should not be overlooked. In certain situations, manual data acquisition may still be necessary, especially when dealing with assets in remote or challenging locations (Moselhi et al., 2020). Additionally, human intervention can provide valuable contextual information that may not be captured through sensors alone. Therefore, a balanced approach that combines both manual and automated data acquisition can provide the most comprehensive insights for decision-making.

4.6.3 Couple

The focus of this step is the formation of Information Couples. To establish a connection between digital and physical assets, it is crucial for each component of a physical asset to have a corresponding instantiation within the digital asset. Here, instantiation refers to the digital counterpart of a specific physical asset, deliverable, resource, or method (Boschert and Rosen, 2016). Depending on the purpose of the coupling, these digital instantiations can be labeled as an ‘instance’ of a given data set, either in an abstract or detailed form. Regardless, it is essential for digital instantiations to provide informative and accurate representations, especially when users are seeking a computational rendition of reality (Ekbia, 2008). Continuous information coupling between components of a physical asset and their digital counterparts within the digital asset leads to the emergence of what is known as an "Information Couple." This concept includes both physical and digital data, but it is not considered as an asset or resource on its own. Instead, it represents the interpretation of information that has been linked from physical and digital built assets and resources. The formation of Information Couples can be facilitated by tracing the flow of information between the physical asset and its digital counterparts. This not only enhances operational efficiency, but also ensures that the insights derived from the digital assets accurately reflect the real-world performance of the physical assets. Ultimately, it enables organizations to make informed decisions, optimize maintenance schedules, and allocate resources effectively, resulting in cost savings and improved productivity.

4.6.4 Use

The final step in the coupling process involves effectively utilizing the coupled information throughout the different stages of the asset's lifecycle. Users may adopt various approaches for utilizing the data accumulated within Information Couples (Pinheiro and Goguen, 1996). Selective extraction allows users to focus on specific types of data or relationships, enabling them to extract the desired information without investing time in other alternatives. Interactive extraction allows users to explore a significant volume of data within an Information Couple and experiment with different paths to enhance the navigation experience. On the other hand, non-guided extraction gives users the freedom to move between different data points and exercise control over the data selection. There are no predefined paths to follow in non-guided extraction, making it suitable for users who already have a clear idea of what and how they want to extract. The interactive nature of Information Couples unlocks new possibilities for exploring data from different angles, zooming in on specific areas of interest, and interacting with objects or elements within the virtual environment. This level of interactivity promotes a deeper understanding of complex data structures and facilitates better decision-making processes.

4.7 Coupling enablers

Coupling enablers refer to the potential technologies that are needed to operationalize lifecycle Information Couples. These enablers can be categorized into five main groups (Qi et al., 2021): (i) tools for the physical world, (ii) tools for modeling digital assets, (iii) tools for connecting physical and digital built assets, (iv) tools for managing coupled information, and (v) tools for the serviceability of Information Couples.

4.7.1 Tools needed for data collection from the physical world

In the practical applications of Information Couples, a comprehensive understanding of the physical world requires technologies that can comprehend and manipulate the tangible space. Tools for recognizing and interacting with the physical world include a wide range of devices and systems, each with a specific purpose in bridging the gap between reality and the digital space.

The integration of IoT devices has revolutionized construction site management. These devices include sensors embedded in equipment, machinery, and building materials. By gathering and transmitting real-time data, IoT devices enable predictive maintenance of machinery, ensuring efficient operation and minimizing costly downtime. Drones equipped with advanced cameras and LiDAR technology provide another notable example. In construction, drones offer a bird's-eye view of project sites, capturing high-resolution imagery and generating accurate topographical maps. This aids in site analysis, progress monitoring, and quality control. Augmented Reality (AR) has also made its mark in the built asset industry. AR overlays digital models onto the physical site, facilitating precise on-site decision-making. Architects, engineers, and contractors can use AR glasses to visualize building components within the context of the construction site. This aids in verifying design accuracy and streamlining communication among different teams.

4.7.2 Tools needed for modeling of digital assets

The modeling of digital assets requires a multifaceted approach that draws upon a variety of advanced tools and techniques to ensure a high level of fidelity to their real-world counterparts. By incorporating principles from computer graphics, machine learning, complex algorithms, and physics simulations, experts can model physical assets, their natural movement, reactions to external stimuli, and environmental interactions. This results in a level of realism that blurs the line between the physical and digital realms. BIM authoring tools are the most common solutions for simulating and visualizing digital assets across different phases of the lifecycle. Currently, numerous software developers, such as Autodesk and Bentley, offer their products as cloud-based solutions, facilitating cloud modeling and computing within CDEs.

4.7.3 Tools needed for connection between physical and digital built assets

To enable a seamless and bi-directional connection between physical and digital assets, the implementation of dedicated communication networks becomes crucial, particularly for remote activities (Grieves and Vickers, 2017). The choice of an appropriate communication network depends on various factors, such as the geographical context, data transfer rate, cost considerations, and operational range (Shen et al., 2008). With the transition toward 5G networks and beyond, there is a significant improvement in real-time information coupling. This is characterized by faster transmission speeds, reduced latency, enhanced security in connections, and decreased power usage. 5G networks enable information couples to establish feedback loops with higher speed and bandwidth, providing insights into the Coupling State across diverse conditions. When combined with advanced technologies such as Artificial Reality (AI), AR, and Virtual Reality (VR), 5G networks can greatly accelerate the exchange and transformation of information among couples.

4.7.4 Tools needed for management of coupled information

Once data are gathered from physical or digital spaces, data processing tools are needed to convert raw data into actionable insights. This involves filtering out noise, calibrating for accuracy, correlating data sets, and storing refined data for potential services. To effectively retain and understand interconnected data and their complex relationships, artificial neural networks (ANNs) and simulated neural networks (SNNs) can be deployed for predictive and automation purposes. ANNs rapidly identify collected data such as images, videos, and codes from physical assets, and learn from inputs based on mathematical functions (Stojanovic, 2021).

Revealing complex relationships within data sets can be facilitated by the use of data mining and machine learning tools, such as platforms like scikit-learn and RapidMiner. These platforms analyze correlations within an organization's data and provide predictive analytics. To efficiently manage the storage of collected data, Cloud platforms like Amazon Redshift, Google BigQuery, or Microsoft Azure SQL Data Warehouse offer scalable and secure data storage (Zhong et al., 2022). Users can utilize these services to store large volumes of refined data, making it easily accessible for future analyses and enabling real-time collaboration among remote teams.

4.7.5 Tools needed for serviceability of Information Couples

Serviceability of information couples refers to the effective use of interconnected data from various sources, ensuring that this coupled information can be efficiently accessed, managed, and utilized for decision-making processes (Qi et al., 2021). The full serviceability of coupled information can be achieved through resource services, knowledge services, and application services (Qi et al., 2021). Resource services, the foundation of information coupling, rely on advanced technologies to gather, transmit, and process data from physical and digital assets.

Knowledge services play a crucial role in improving decision-making by providing stakeholders with a deeper understanding of asset performance, optimizing operational efficiency, and reducing downtime through predictive maintenance strategies. Examples of knowledge services include data analytics platforms such as PowerBI and QlikView, predictive analytics software like IBM SPSS, RapidMiner, and SAS, as well as collaborative data science platforms such as dataRobot and Domino Data Laboratory.

Application services, on the other hand, contribute to the coupling of information by offering user interfaces, simulations, and visualization tools. Technologies such as AR, VR, Mixed Reality (MR), and Extended Reality (XR) enable users to immerse themselves in a virtual representation of the physical asset (Dawood et al., 2009), enabling intuitive interaction and real-time monitoring.

4.8 Coupling metrics

At level 2 of the proposed taxonomy, coupling metrics facilitate the measurement, assessment, and evaluation of various dimensions concerning the operational and representational coupling of built assets and resources. Operational metrics are defined to gauge the effectiveness of Information Couples throughout their lifecycle. These metrics assess factors such as the degree of coupling between built assets and resources, the scale of assets involved in coupling actions, the level of automation, and the functional reliability of the Information Couples. Table 2 outlines potential metrics for evaluating the operation of Information Couples. Representational coupling pertains to the characteristics of digital representation. The proposed metrics assess the transparency, fidelity, accuracy, complexity, or deficiencies of a representation. The hierarchical organization of representational coupling metrics is detailed in Table 3.

5 Discussion

The research project's primary objective was to identify and define the essential dimensions and characteristics required to enable the coupling of physical and digital built assets and resources. The proposed taxonomy aims to bridge the gap between existing knowledge and anticipated advancements in the field, providing a comprehensive tool for academics and industry practitioners. It goes beyond project-specific considerations and accommodates a broad spectrum of theories and concepts related to digital

Table 2 Operational coupling metrics

Metric	Description	Reference
Coupling level (CLevel)	The extent of connectedness between the physical and digital built assets can be described by CLevel. An elevated CLevel represents the tight couplings and any changes in one asset may affect another in a real-time manner. CLevel comprises five levels as follows: • No Coupling: indicates no interaction or connectivity between assets or resources. • Low Coupling: represents minimal interaction where changes in one asset or resource slightly affect the other, typically in a non-real-time manner. • Medium Coupling: characterizes moderate interaction with some real-time data exchange and interdependencies. • Medium-High Coupling: denotes a higher level of interaction with significant real-time data exchange and dependency, leading to more synchronized operations between the assets. • High Coupling – Mirroring: refers to a fully integrated state where changes in one asset or resource are instantaneously reflected in the other, mirroring each other's state in real-time.	Succar (2023)
Asset scale	The relative size of an asset for coupling purposes, ranging from a small part (e.g., door handle) to larger scales such as a country (e.g., region, province) or the entire world (e.g., planets).	Succar and Poirier (2020)
Dynamic sub-scales (System)	Refers to systems which are more/less granular than assets. Systems are capable to enhance information coupling of deliverables, resources, and requirements of physical and digital built assets across multiple domains such as geographic information system (GIS), product lifecycle management (PLM), and BIM. Similar to asset scale, system sub-scales span from world system (e.g., GPS system) to component system (e.g., fan coil system).	Succar (2023)
Degree of automation (DoA)	Determines the extent of automation as physical and digital assets are coupled. DoA includes five degrees: • Manual: operations are entirely human-driven with no automation. • Assisted: human operations are supported by basic automated tools or systems, reducing manual effort. • Automated: systems perform tasks with minimal human intervention, but human oversight is still required. • Automatic: tasks are performed automatically without ongoing human oversight, but human intervention is possible if needed. • Autonomous: complete automation where systems operate independently without any human intervention, even in decision-making processes.	BIM dictionary (2023)
Functional reliability	Determines to the ability of an information couple to perform the intended tasks correctly, completely, and rightfully with an acceptable and admissible results. "Correctness" of functional reliability refers to a failure-free function. A reliable function should also satisfy the "Rightness" of a digital asset in comparison to its physical counterpart in terms of status, property, and position. "Completeness" means having all necessary parts, components, and condition to perform a reliable coupling action.	Zhang et al. (2021); Shubinski and Schäbe (2013)

Table 3 Representational coupling metrics

Metric	Description	Reference
Representation fidelity (RT)	Refers to extent of faithfulness of a representation that is being used for coupling purposes. A digital model is faithful when it correctly mirrors different attributes of its coupled physical asset. As representation Fidelity increases, users can trust representations more and use them for automatic decision making. A faithful representation should be complete (having all detailed parts and components of a physical object), meaningful (having all useful semantics within a model), clear (clear representation of external structures and internal behaviors of the physical object), correct (error free geometrical/technical representation), and abstract (a model that covers different features of a physical object from different viewpoints).	Burton-Jones and Grange (2013); Zhang et al. (2021)
Level of accuracy (LoA)	Specifies how accurately a digital model represents properties and structure of a physical asset. Level of accuracy (LoA) is a high-level metric which addresses measurement accuracy such as LoA10, LoA50, and etc. Transformational accuracy such as accuracy in transforming simulation-based algorithms to human-readable model and representation Accuracy such as USIBD Standard Deviation.	Zhang et al. (2021); USIBD (2016)
Complexity	It is favorable to keep a digital model as simple as possible. Unnecessary complexity of a model is caused by its high representational fidelity. The model's structure along with its components and variables defines the complexity. Yet, it is difficult to examine complexity of a digital model through quantitative index. The complexity can be qualitatively measured by underlying the negative impacts of coupled information in assist's lifecycle (e.g., poor performance in reuse or maintenance phase). Therefore, simplicity of the digital model should be considered, especially when representing large and complex assets.	Zhang et al. (2021)
Degree of correspondence	Specifies how closely properties of a physical asset are mapped into its digital representations. Symbolic correspondence is mapping the characteristics of a physical asset in a very abstract way. On the contrary, literal correspondence entails closely mapping a physical asset into digital representation without the use of metaphors or allegories.	Price (2008)
Degree of transparency (DoT)	Measures the content accessibility of users to the coupling process, including structure of digital representations and their conceptual or physical counterparts. Increasing of representation transparency provides users the feeling of competence, trust, and control over built asset information coupling. This results in effective interaction between Information Couples and users with a high level ofproductivity.	Burton-Jones and Grange (2013)

representations, digital twinning, and asset traceability.

In today's interconnected world, where projects often involve a multitude of information sources and databases, the task of determining which information should be coupled and which should remain uncoupled becomes increasingly complex. Furthermore, the rapid advancement of technology has led to a significant growth in the types of enablers, further complicating the decision-making process. This research aims to address this complexity by developing defined dimensions and characteristics of asset coupling, drawing on various overlooked pieces of knowledge in the context of CPS and DT. The resulting taxonomy comprehensively covers the various types of information coupling, from the initial intent to deliver an asset, through its operational milestone, to its potential for reuse. This taxonomy provides a valuable framework for all disciplines to better understand which information should be coupled with specific milestones, thereby facilitating the effective management and utilization of built assets and resources.

While previous works have offered valuable insights into the notation of digital twinning and its applications in information management of built assets, they have often been limited to specific lifecycle stages or focused on particular use cases of asset coupling, such as operational data management or performance monitoring. However, the taxonomy presented in this research takes a more holistic view by considering the entire lifecycle of the asset, from conceptualization to disposal or recuse. It recognizes the importance of having a comprehensive understanding of what, when, and how information should be coupled and measured across different stages. Furthermore, the taxonomy offers a robust structure that is not only relevant to the current state of technology but also adaptable to embrace future advancements. This adaptability is crucial in a landscape where digital tools and methodologies evolve rapidly, and legacy systems often struggle to accommodate new types of data and modes of interaction.

Previous research has often overlooked the categorization of primary reasons and expected outcomes associated with asset coupling throughout different phases of the lifecycle. This paper proposes that a well-defined purpose for asset coupling has the potential to enhance the value and efficiency in the planning, delivery, management, and utilization of built assets. It is important to note, however, that while asset coupling can be significant in certain contexts, the success of project management is not solely dependent on it. Various factors contribute to the effectiveness of managing built assets, and the role of asset coupling should be seen as one of several elements that may influence the overall process. The value of such categorization lies in the potential for decision-makers, property owners, and contractors to gain a better understanding of the main benefits of coupling lifecycle information. Therefore, one of the primary objectives in developing the taxonomy was to identify common coupling purposes and outcomes in relation to other aspects of asset coupling. Furthermore, a review of prior research has revealed that designers, contractors, and property owners often face challenges when identifying the necessary steps and actions to create information couples (Bailey et al., 2012; Juarez et al., 2021; Price, 2008). To implement asset coupling effectively, a holistic approach was proposed to operationalize the key dimensions of the taxonomy. The Coupling Action can serve as a procedural guide that outlines step-by-step processes for creating various types of information couples. Defining clear steps and processes for coupling built assets and resources can promote collaboration among all parties, simplify information management, and facilitate adaptation to evolving technologies (Sacks et al., 2020; Zhang et al., 2021). The Coupling Action dimension is not mutually exclusive; rather, it should coexist with other dimensions within the taxonomy. In fact, it is crucial to view the Coupling Action as an integral part of a framework rather than isolating it as a standalone dimension. For example, the proposed Coupling Metrics and Coupling Enablers can potentially exist at each step of the Coupling Action. This allows users to evaluate both the representational and operational coupling of built assets and identify the necessary tools to facilitate these couplings.

The proposed taxonomy offers a strategic approach to information management. It defines potential dimensions and characteristics of asset coupling, providing guidance to industry practitioners in managing lifecycle data and serving as a reference for identifying key requirements and steps in developing DT-based models. Users can also use the taxonomy as a guide to make informed decisions about information coupling at each stage, optimizing resource utilization, automating systems, and improving asset management efficiency.

Another potential application of the proposed taxonomy is evaluating organizational readiness for adopting DT-based solutions. By leveraging the taxonomy's dimensions, small and medium-sized enterprises (SMEs) can evaluate their current capabilities and identify areas that require enhancement to support digital transformation. This proactive evaluation enables SMEs to chart a strategic course, focusing on acquiring necessary deliverables, digital tools, upskilling staff, and aligning business processes with digital standards. When assessing readiness, SMEs can prioritize investment in high-impact areas, ensuring an efficient and effective transition to digitalization.

5.1 Research limitations

This research primarily relied on literature reviews and the examination of best practices to gather and classify data. It is important to acknowledge the potential presence of data biases. Specifically, information related to newly developing technologies, theories, frameworks, or models that had not been officially published or completed during the study's timeframe was omitted from the data analysis.

Developing a comprehensive taxonomy in the context of the built asset industry required amalgamating knowledge and concepts from multiple disciplines, such as civil engineering, data science, and economics. The inherent diversity across these fields presented a significant obstacle, as bridging the gap and ensuring the taxonomy's comprehensibility and relevance to experts from distinct backgrounds required substantial effort. Therefore, it is essential to further validate the data biases by experts from various disciplines.

Addressing the validation and testing phase in the development of the taxonomy was identified as a noteworthy limitation in this research. The comprehensive real-world validation and testing that was needed demanded substantial time, resources, and access to diverse data sets representing various types of built assets and resource coupling scenarios. This limitation restricted the ability to thoroughly assess the effectiveness, accuracy, and usability of the taxonomy in different practical contexts. To overcome this limitation, careful planning and the inclusion of case studies or pilot implementations are necessary to provide valuable insights into the performance and applicability of the taxonomy in real-world scenarios.

6 Conclusions and future works

This paper reviewed the current state of asset coupling to determine the essential dimensions and characteristics required to support the lifecycle information coupling of built assets and resources. Building upon existing works in the literature, a broader vision was adopted to understand the key models, definitions, and characteristics that facilitate asset coupling across different lifecycle stages. As an emerging field of study, this research organized the dispersed and vague characteristics of asset coupling found in literature into a taxonomy of built asset lifecycle information coupling. Additional dimensions and characteristics were conceptualized to assist in the creation of Information Couples, monitor the state of asset coupling, assess the operational and representational behavior of Information Couples, and evaluate their impacts through the lens of SDGs. The versatility of the taxonomy ensures practicality in current practices, adaptability to new technologies and practices, and the ability to guide stakeholders through the complexities of physical and digital coupling. It serves as a reference to define, measure, and manage the coupling of physical and digital assets, enabling more informed decision-making and optimized asset management. The implications of this research are significant, offering both a theoretical contribution to the field and practical guidance for industry application. The proposed taxonomy serves as a foundation for future research and a guide for practitioners, ensuring that the coupling of lifecycle information is not just a technical exercise, but a strategic endeavor that enhances the value and performance of built assets.

As a result, the next steps in this endeavor involve advancing the taxonomy by addressing its current limitations. These steps include conducting tests on the proposed taxonomy with a curated panel of industry experts, gathering up-to-date information from various domains involved in the asset coupling process, and implementing practical scenarios to showcase how the taxonomy effectively addresses challenges within the built asset industry. A subsequent paper will be presented in the future to present the validation of this study and report the results of the testing and evaluation of the proposed taxonomy. Additionally, the next steps involve the development of a coupling action instantiation framework that will help determine the practicality of the research findings in real-world scenarios, as well as provide insights into its potential for widespread adoption.

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