



ENABLING COGNITIVE DIGITAL TWINS IN HEALTHCARE: DATA TYPES AND APPLICATION INSIGHTS FROM MACHINE LEARNING RESEARCH

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Abstract

Cognitive Digital Twins (CDTs) emerge as an evolution of the Digital Twin (DT) concept, incorporating cognitive capabilities to enhance data-driven decision-making in complex and dynamic systems such as healthcare facilities. The integration of machine learning (ML) promises a transformative approach to healthcare facility management (HFM). This study explores key data types and application areas relevant to CDT development, derived from a review of ML implementations in healthcare. The findings categorize data types, including health records and appointment data, alongside application areas involving decision support and waiting time prediction. These insights provide a novel foundation for CDT-driven healthcare solutions, enabling proactive management.

Introduction

The healthcare industry has been undergoing significant transformations with the increasing adoption of digital technologies to adapt to the changing needs in the sector. Integrating new technologies concerning facility management (FM) and operational aspects is an ongoing challenge for the National Health Service (NHS) of the UK at various scales. DTs for healthcare facilities are regarded as promising technological advancements that enable seamless data flow and therefore support real-time monitoring, sensing, and controlling and data-informed decision making (Madubuike and Anumba 2021).

Advancements in technology allow systems to become more intelligent and interconnected through sophisticated mechanisms of data collection and data sharing that lead to complex datasets. The interconnectivity of such systems is a matter of semantic technologies. Studies on DT systems focus on semantic interoperability at the machine-readable ontology level to enable this interconnectivity. To model a DT system, it is necessary to model domain knowledge with an ontological layer. This poses a fundamental challenge to effectively create the necessary knowledge from the growing datasets. With that challenge at hand, systems with increased cognitive abilities emerged as a need to extract meaningful and useful information and support decision making, and in

fact, CDTs are regarded as ontologically enriched DTs. CDTs can be thought of as distributed cognitive systems that involve all subsystems of its physical counterpart. CDTs offer significant potential in HFM to enhance operational efficiency, patient care, and overall system performance, and is an unexplored area. Considering that FM covers 80% of a building's life cycle phase, the adoption of advanced technology in healthcare FM will have a significant impact on the effective and efficient operation and management, and more importantly, on the well-being and satisfaction of patients.

Problems and Challenges in Healthcare FM

HFM has some unique challenges due to its highly complex socio-technical nature, namely patient needs, staff workflows, visitors, and technological advancements. The management of such facilities aims to maintain a balance between providing quality patient care and optimizing operational efficiency. Operation and maintenance work should be conducted smoothly and without causing any disruption to healthcare activities. Otherwise, this can lead to vital results for patients. Another challenging aspect is that healthcare facilities can be considered as spaces of unexpected scenarios. Facilities should be prepared to handle emergencies or unexpected scenarios effectively and proactively.

In current management practices, inaccurate data and lack of information typically cause challenges concerning information management and eventually decision making. Various types and formats of data cause fragmentation and lead to inefficiencies (Demirdöğen, Işık et al. 2021). The inability to access the right information at the right time can have vital results in healthcare FM. In addition, the lack of effective real-time monitoring and bi-directional information flow due to existing computer-aided facilities management software cause a low level of efficiency.

Traditional or unstructured methods in FM, such as costly and time-consuming information validation and verification with actual site visits, cause delays in service. FM systems such as Computer Aided Facility Management (CAFM), Computer Maintenance Management Systems (CMMS), and Building Automation Systems (BAS) are aimed at supporting

managers in that sense, but these FM systems have drawbacks such as manual data entry, not-user friendly interfaces, and lack of visualization (Shalabi and Turkan

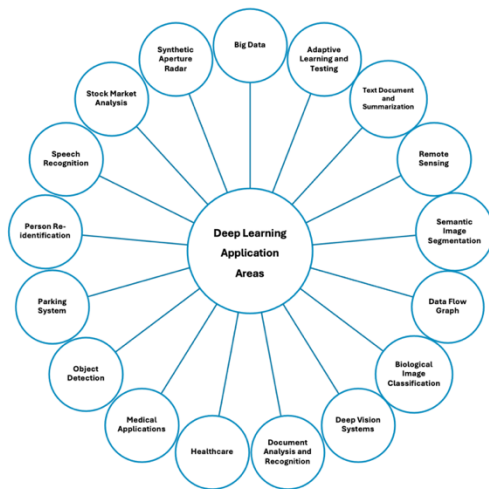


Figure 1: Applications of Deep Learning. Adapted from (Dargan, Kumar et al. 2020)

2017). In addition, each FM system focuses on certain services, requiring the use of various data management platforms. This, in turn, leads to interoperability problems across these fragmented systems (Lu, Chen et al. 2018).

CDTs -regarded as the next step in the concept of the DT approach- are increasingly being studied in various fields in an interdisciplinary manner. Despite the growing interest in CDTs, its potential in HFM is unexplored, which indicates a significant gap in existing literature. Especially, CDTs offer significant potential in overcoming the above-mentioned HFM challenges to enhance operational efficiency, patient care, and overall system performance. These potentials address the need for defining domain-specific data to effectively overcome the above-mentioned data management challenges. To our knowledge, there is no such foundation offered, highlighting another significant gap in the literature.

This paper aims to address these gaps by answering the following research questions:

1. What are the potential applications of CDTs in healthcare facility management?
2. What type of data needs to be acquired for the implementation of ML/DL and predictive analytics within the cognitive layer?

With those questions, the aim of this paper is to systematically review ML/DL and predictive analytics implementations in HFM to inform the cognitive layer of CDTs and specify potential applications and critical data types. Two objectives were established to achieve this: (1) to present the first state-of-the-art and critical review on CDT providing a consolidated view of the applications explored and (2) to present a systematic review of literature on ML/DL and predictive analytics implementations in HFM providing a foundation for the cognitive layer of CDT.

Background of the Study

The management phase of a building is complex and data-intensive and demands an integrated and robust information management system. While systems such as CMMS, CAFM, BAS, and Integrated Workplace Management Systems (IWMS) offer some support in FM, they often lack integration, making it difficult to access and utilize information effectively. The understanding of a DT has evolved from being only an exact representation of physical phenomena towards having an impact on its physical twin. This evolution of DT is highly related to the advancements realized in the field of ML and deep learning (DL). The DL paradigm is the core enabler of the evolution of DTs. The effective use of complex datasets in training models for deep structural learning is realized as a breakthrough in various fields (Dargan, Kumar et al. 2020) (Figure 1).

Evolution of Digital Twins and applications of CDT in industries

In the last ten years, the concept of DT and its functional implementations have evolved rapidly. But in recent years, the concept of DT is criticized as being only a digital shadow of its physical counterpart and expanded to a concept that impacts its physical twin (Sepasgozar 2021). This discussion was further expanded through the development of the CDT notion (Abburu, Berre et al. 2020). Implementation of CDTs can be categorized under 11 main areas: Manufacturing and Industrial Systems, Construction and Built Environment, Energy and Environmental Sciences, Business and Management, Computer Science and Digital Technologies, Aerospace and Transportation Engineering, Software and Systems Engineering, Human-centered Computing and Robotics, Education and Research, AI and Data Science, and lastly Healthcare. Current CDT implementations in healthcare focus primarily on cybersecurity (Xu, Pirbhulal et al. 2024). Even though not named as CDTs, there are a few existing implementations of AI-integrated DTs, such as the proactive remote monitoring services at Philips (Houten 2018), GE HealthCare's Digital Twin technology for informed capacity decisions (GE-Healthcare 2025), and data-driven healthcare solutions of the Mayo Clinic (Prasad 2025). Therefore, this study reviews ML-DL and predictive analytics implementations in HFM to inform the cognitive layer of DTs to enable the future development of CDTs for HFM.

Digital Twins with enhanced Cognition

The cognitive processes and mechanisms of human information processing are sources of inspiration for fields that try to mimic them in cognitive computing. Learning is considered as the core capacity of these cognitive systems (Wang, Widrow et al. 2020). Studies show that mimicking human learning activity requires more than conventional ML mechanisms. Certain cognitive abilities are fundamental for DL capability and reasoning.

Table 1: Definitions of CDT

Author	Notion	Definition
(Al Faruque, Muthirayan et al. 2021)	Cognitive Digital Twin	a DT that includes elements of cognitive science, ML, and AI harnessing implicit knowledge derived from the operational experience of existing manufacturing systems, facilitates the transfer of more effective decision-making and control methods, resulting in enhanced overall performance across the system.
(Eirinakis, Kalaboukas et al. 2020)	Enhanced Cognitive Twin	a DT coupled not only by cognitive (i.e., self-awareness) abilities like anomaly detection and behavioral learning but also with the ability to decide on actions of the physical twin that will improve the metrics characterizing its state or role.
(Rožanec, Jinzhi et al. 2020)	Actionable Cognitive Twin	DTs with entities that describe physical assets and actors as well as how data is ingested into the digital counterpart, leveraged by algorithms and AI, and how are their outcomes linked to advice on potential actions that can be taken to mitigate observed issues to help on decision making.
(Yitmen, Alizadehsalehi et al. 2021)	Cognitive Digital Twin	CDT is envisioned as a robust monitoring and control mechanism and an essential part of the decision-making action that leads to system optimization
(Zheng, Lu et al. 2022)	Cognitive Digital Twin	a digital representation of a physical system that is augmented with certain cognitive capabilities and support to execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components; and evolves continuously with the physical system across the entire lifecycle.

The emergence of CDT is based on studies that explored enhancing the cognitive abilities of DTs. The early definitions of CDT were made by Adl (2016) and Fariz Saracevic (2017) who elaborated on the evolving cognitive abilities of IoT technologies, cognitive computing, and AI. Since then, related studies have introduced enhanced definitions and characteristics of CDTs (Table 1).

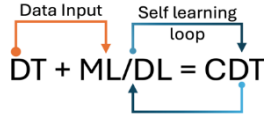


Figure 2: Cognitive Digital Twin Framework

Overall, CDTs refer to the integration of data-driven models generated by Data Analytics and ML into the DT artifact (Eirinakis, Kalaboukas et al. 2020). The study Zheng, Lu et al. (2022) introduces characteristics and definitions of CDT and proposes an implementation architecture. It is claimed that the main difference of CDT from a DT is “CDT should incorporate cognitive features to enable sensing complex and unpredicted behaviors; and reasoning for optimization strategies leading to a system that is continuously evolving.” The characteristic of CDT is listed as being DT-based, cognition capability, full lifecycle management, autonomy capability, and continuously evolving. Depending on these characteristics, the authors define CDT as “a digital representation of a physical system that is augmented with certain cognitive capabilities and support to execute autonomous activities; comprises a set of semantically interlinked digital models related to different lifecycle phases of the physical system including its subsystems and components; and evolves continuously with the physical system across the entire lifecycle.”

CDTs offer the combination of DT systems with cognitive learning and predictive analytics. By integrating ML and DL models into DT systems, the novel intelligent system evolves through a self-learning loop and can identify, forecast, and react to its physical counterpart (Figure 2).

Research Methodology

A systematic review process was conducted following a qualitative content analysis (Figure 3). Scopus and Web of Science were used as the main literature databases. First, the content of the final set of publications was categorized under certain themes, and secondly, findings were classified under superordinate and subordinate classes within a hierarchical order based on the similarities of (1) data types and (2) application areas. The predefined coding scheme for content analysis consists of applications, programming languages, data preprocessing

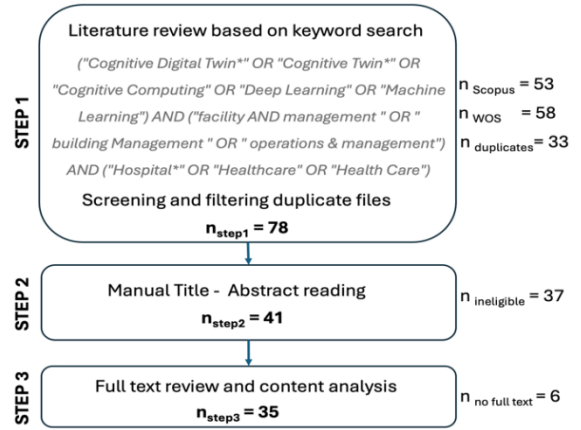


Figure 3: Research Process Workflow

methods, algorithms, data types, and model performance evaluation methods. However, this paper focuses on the applications and data types of reviewed studies and also maps relevant algorithms with the identified data types.

This paper brings novelty with a comprehensive classification of (i) ML and DL applications in healthcare and (ii) the data types to inform the cognitive layer of CDTs.

Machine Learning Applications in Healthcare Facility Management

Organizations depend on FM to incorporate people, places, and processes into the built environment. Currently, the built environment and FM are seeing rapid advancements and increasing innovation with the inclusion of advanced technology (Li, Zhang et al. 2019). There has been a dramatic shift in FM digitalization in response to the world's fast transition to digital. A new era for the FM industry is being defined by technologies such as ML, artificial intelligence (AI), the Internet of Things (IoT), and sensors. ML integrated CDTs promise various applications for the management of healthcare facilities and healthcare operations. Based on the current AI and ML integrations into the operations and management of healthcare, and the emerging concept of CDTs and its application in various other fields, CDTs can be implemented for decision support, strategic healthcare planning, patient flow management, waiting time prediction and delay management, resource and capacity management, appointment scheduling, improving patient experience and staff engagement, and lastly, hospital readmission and workload prediction (Figure 4).



Figure 4: Healthcare related applications in ML and predictive analytics studies

Decision support for strategic management in healthcare

Decision support studies consider the operation of a healthcare facility from a general aspect, covering most of the other application areas described in this paper. Some research focus of decision support studies are referral process and long-term care discharge planning. The study Chuang, Zargoush et al. (2023) proposes a prediction-driven decision support system for discharge optimization enabled through a framework in which ML algorithms are combined with optimization models. Such studies greatly inform the cognitive layer on building ML algorithms for predictive analytics.

Strategic healthcare planning

Some studies consider ML and optimization processes in healthcare operations applications at the policy, hospital, and patient levels (Misic and Perakis 2020). For a brief overview, policy-level applications focus on healthcare costs (Aswani, Shen et al. 2019), proposing estimation

methodology based on inverse optimization, dynamic allocation policy (Bertsimas, Farias et al. 2013), approached as a linear optimization problem, individual-level intervention effects (Gupta, Han et al. 2020), formulated as a robust optimization problem. Hospital-level applications consider staffing and scheduling rooms for surgeries (Rath and Rajaram 2018), where scheduling is formulated as a two-stage robust mixed-integer optimization problem, and staffing decision improved through a two-stage integer stochastic dynamic program. There are also studies on reducing the maximum average occupancy through a large-scale optimization model (Zenteno, Carnes et al. 2016). In patient-level studies, analytics methods are applied to dosing (Bastani and Bayati 2020), personalized drug treatment (Bertsimas, Kallus et al. 2017) in certain therapies. Patient-level studies significantly inform the CDT field in terms of how the increasing amount of electronic health data could successfully be used for training models. Such studies provide a strong background for the application of data analytics in a CDT system.

Patient flow Management

Patient flow analysis is a significant decision-support mechanism in HFM, as it provides feedback on overcrowding, length of stay, clinical pathways, and overall system performance. Patient flow simulations have been widely studied; however, ML integration using the big data of electronic health records shows significant potential to improve the heterogeneity problem of existing simulation models. In the study of Abuhay, Robinson et al. (2023) patient flow was approached as a time-series problem, and the Auto-Regressive Integrated Moving Averages (ARIMA) and Prophet were used for the prediction model. There are also various other formulation proposals, such as clustering (Prokofyeva and Zaytsev 2020), or classification (Kovalchuk, Funkner et al. 2018). Such studies provide information on how to construct ML integrated patient flow models. Arnolds and Gartner (2018), on the other hand, introduces an ML algorithm based on probabilistic finite state automata (PFSA) to learn from clinical pathway data and inform future layout planning to minimize distances traveled by patients. As an example of data-driven clinical pathway mining, the proposed method informs the learning process within the cognitive steps, model formulation, and evaluation methods. Other studies that focus on data-driven patient flow prediction propose regression and tree-based methods (Bertsimas, Pauphilet et al. 2022), and learning classification systems that use Convolutional Neural Networks (Ghaemifar, Ebadollahi et al. 2024).

Waiting time prediction and delay Management

Successful waiting time prediction can increase patient satisfaction, resource management, improve the quality of care, and increase transparency and trust in the healthcare system. Studies propose Random Forest algorithm (Al-Mousa, Al-Zubaidi et al. 2024), quantile regression forest (Arora, Taylor et al. 2023), ML-based queueing system (Carmeli, Yom-Tov et al. 2023), elastic net ML algorithm (Curtis, Liu et al. 2018), quantile regression and ML

algorithms such as ridge regression, LASSO regression, and random forest (Pak, Gannon et al. 2021) for accurate prediction of waiting time and delay management. Such studies are significant in terms of integrating queuing systems into the CDT processes and enhancing prediction accuracy.

Resource and capacity management

Resource and capacity management studies focus on process improvements, effective use of clinic capacity, bed allocations, and change management. The data-based approaches in these studies propose ML algorithms such as decision tree (Pachamanova, Tilson et al. 2022), time-series forecasting, regression-based methods, and Artificial Neural Networks with several typologies (Schäfer, Walther et al. 2023). The complexity of the dynamic healthcare environments and the requirement of efficient real-time planning and decision-making are also acknowledged and addressed in the studies mentioned.

Appointment scheduling

The above-introduced aspects are significant for developing effective and efficient healthcare service delivery. Another crucial aspect, appointment scheduling, is highly related to the productivity and efficiency of the healthcare system, having a direct impact on waiting times, patient experience and satisfaction levels, and financial profits of the clinic (Seyedi, Eshghi et al. 2024). Studies in the field of AI and ML suggest that predictive analytics can be used to forecast patient demand, facilitating proactive adjustments to scheduling and allocation of resources. This can lead to personalized appointment scheduling in future studies. The study Feng, Jia et al. (2023) is a significant contribution to this field, providing an open-source rich data set that can be used for further model development. Samorani, Harris et al. (2022) proposes a race-aware methodology based on a combination of LASSO and logistic regression. Another inspiring study is the proposed Alternating Direction Method of Multipliers (ADMM)-based solution Method for developing a centralized appointment scheduling system (Seyedi, Eshghi et al. 2024).

Improving patient experience and staff engagement

Patient experience is regarded as a key quality indicator for healthcare services and is impacted by various factors. Similarly, staff engagement is crucial for success in an organizational level and is driven by a range of factors. In that sense, there are studies that focus specifically on factors influencing patients experience, drivers of staff engagement, and drivers for patients' satisfaction. The study of Al Nuairi, Simsekler et al. (2023) proposes a data-driven Bayesian belief network model using tree augmented Naive Bayes structural learning algorithm. Results show that confidence and trust, respect for patient-centered values, preferences, and expressed needs, and emotional support are the most influential factors for patient experience. On the other hand, Simsekler, Alhashmi et al. (2021) states that demographics are most influential factors for patient satisfaction during the registration stage. This study uses

an estimation model developed with the tree-based ML algorithm, random forests.

Hospital readmissions and workload prediction

Workload prediction is significant to avoid overcrowding in healthcare environments and decrease waiting times, as well as to ensure optimum staffing and resource allocation. The study Guan and Engelhardt (2019) aims to estimate the volume of sick patients in the pediatric outpatient clinic by comparing several models. The study concludes that the Recurrent LSTM neural network-based estimation model outperforms others. Also, DL approaches are researched for Work Relative Value Units, which indicate the amount of effort a consultant makes for the care of a patient. In the study of Joseph, Leventhal et al. (2023) a combination of a four-layer deep neural network and an LSTM network is used, and the output is fed into a final prediction output neuron. Findings of this study reveal that DL algorithms are promising for such predictions. Another admission-related study Somanchi, Adjerid et al. (2022) that aims to predict the admission or discharge of patients applying to emergency departments (ED) and introduces a two-stage Prediction Framework.

Data Types in Healthcare FM-Related ML and Predictive Analytics Studies

Based on our review of the existing literature on ML and predictive analytics implementation for HFM-related problems, four main types of data are considered key for management-related ML and predictive analytics studies:

- Operational and facility data
- Patient-level data
- Survey and qualitative data
- Predictive and event-based data

This categorization is structured based on commonalities of data described in the studies reviewed. Therefore, reviewed studies are likely to present various data types that fall under different categories.

Operational and facility data

Operational and facility data includes hospital resource management data such as hospital operations data (Arnolds and Gartner 2018, Pachamanova, Tilson et al. 2022), staff allocation, and capacity data (Helm, Alaeddini et al. 2016).

Appointment scheduling related data primarily involves appointment registries of patients and patient no-show rates (Samorani, Harris et al. 2022, Seyedi, Eshghi et al. 2024). Few studies focus on the use of department specific appointment and imaging data (Curtis, Liu et al. 2018, Cho and Hong 2023). In terms of departments, ED data is widely studied in ML related prediction studies. Acquired data types are patient arrival trends and ED workload data (Somanchi, Adjerid et al. 2022). Finally, queuing and service flow data datasets are used for prediction models (Al-Mousa, Al-Zubaidi et al. 2024).

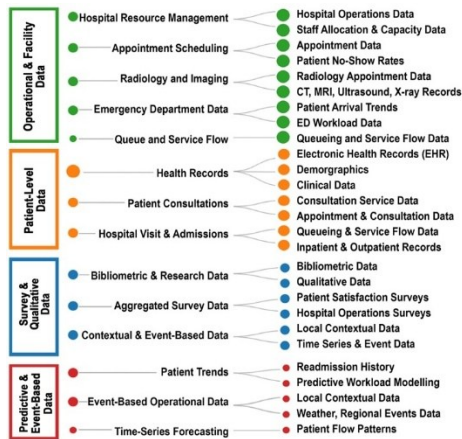


Figure 5: Data Types in Healthcare FM Related ML and Predictive Analytics Studies

Patient-level data

Patient-level data is widely used for training models that these are usually big datasets acquired and stored by healthcare systems and local care providers. These are health records, including Electronic Health Records (EHR) of patients, demographic data, and historical clinical data (Helm, Alaeddini et al. 2016, Guan and Engelhardt 2019, Pak, Gannon et al. 2021, Chuang, Zargoush et al. 2023, Joseph, Leventhal et al. 2023). Patient consultations are also a source of data, including consultation service data, and patient-level appointment and consultation data (Guan and Engelhardt 2019, Samorani, Harris et al. 2022, Chuang, Zargoush et al. 2023). Lastly, in a patient-level, recordings of hospital visits and admissions, including queuing and service flow data, and inpatient and outpatient data are sources for healthcare FM related ML studies (Somanchi, Adjerid et al. 2022, Joseph, Leventhal et al. 2023).

Survey and Qualitative data

There are review studies stating bibliometric analysis of decision support systems and presenting qualitative data analysis of interviews (Al-Nammari, Simsekler et al. 2023, Carmeli, Yom-Tov et al. 2023, Joseph, Leventhal et al. 2023). Also, aggregated survey data is widely used in such studies based on patients' satisfaction surveys and hospital operations surveys (Al Nuairi, Simsekler et al. 2023). Local contextual data and time series or event data are also presented as survey results or qualitatively analyzed data.

Predictive and event-based data

Data types that fall under this category are patient trends, event-based operational data, and time-series forecasting data. Patient trends data include readmissions historical data of patients and predictive workload modelling data, whereas event-based operational data consists of local contextual data and data such as weather and regional events (Feng, Jia et al. 2023, Schäfer, Walther et al. 2023). Lastly, in terms of time-series forecasting patient flow patterns are mentioned in related studies (Pachamanova, Tilson et al. 2022).

Conclusions

The healthcare industry has been undergoing significant transformations with the increasing adoption of digital technologies to adapt to the changing needs in the sector. One of the main objectives of CDT is the efficient use of data, contributing to the smart data paradigm. Therefore, domain-specific knowledge representations at the ontology level derived from interoperable data types are necessary to contribute to this common objective and adapt CDTs into healthcare. This study emphasized the foundational data types and application areas essential for developing CDTs in HFM, derived from existing ML implementations. For future studies, some of the main challenges are as follows: (1) Data privacy, security, and ethical considerations due to working with health data and sensitive patient data, and (2) interoperability of data formats and systems. Data management is a major phase within a CDT system that consists of collecting, processing, storing, modelling (knowledge graphs), and analyzing the data. To embed the defined data types into CDT systems, data management needs to be considered starting from the top-level ontologies to ensure seamless integration and interoperability among domain-specific data.

Acknowledgements

This research is funded by a studentship from The Northern Bridge Consortium, supported by the UKRI-Arts and Humanities Research Council (AHRC).

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