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AI-Augmented Project Portfolio Digital Twin for Dynamic Capacity, Dependency, and Risk Management: A Systematic Review

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ABSTRACT

Project portfolios in engineering, construction and technology firms experience resource sharing, complex cross-project relations, and correlated risks, and even though they are managed by a shared resource pool, project decisions are primarily made based on those static, periodic reports. Based on the available peer-reviewed literature published from 2001 to 2024, this systematic review brings together six streams of literature: digital twin foundations, built-environment twins, organizational twins, portfolio and risk governance, artificial intelligence (AI) for project management, and planning and dependency modelling, to develop the conceptual and technical basis of an AI-augmented project portfolio digital twin. Sources were classified in terms of capacity, dependency functions and in terms of the integration of the digital model, digital shadow and digital twin. The synthesis reveals that despite being conceptually unified, classified implementations still remain dominated by digital shadows (35%) and digital models (28%). From the survey of 175 to 182 firms, portfolio research evidence is strong on the link between front-end quality and portfolio success, and strategic control and portfolio risk management. AI evidence is wide-ranging – one scientometric review includes 4,473 articles – and expert opinion highlights schedule, cost and risk management as knowledge areas that are most vulnerable to AI. Proposed a 5-layer reference architecture for the resource constraint scheduling, RSM propagation and AI forecasting in a closed loop, predict and decide loop. Some estimates suggest that ignoring the dependencies would result in approximately 55% underestimate in aggregate exposure and approximately 10 months in the completion time of the P80 exposure. The key issues to overcome are data integration, model fidelity, explainability, and the value for these stakeholders.

Keywords: *Artificial Intelligence; Design Structure Matrix; Digital Twin; Organizational Digital Twin; Portfolio Risk Management; Project Interdependencies; Project Portfolio Management; Resource Capacity Planning; Resource-Constrained Project Scheduling*

INTRODUCTION

Project-based organizations provide strategy with a series of projects that are run concurrently and share specialists, equipment and budgets. In these environments, cost overruns are seldom attributed to one-off occurrences; they are more likely to develop due to the interdependencies that spread among complexity and risk factors affecting activities and projects. A fuzzy hybrid approach, such as fuzzy analytic network processing, fuzzy neural networks and fuzzy simulation, proved to be the most prevalent method in previous AI-based risk assessment studies, as it could model uncertainty, but it was limited in its application due to the subjective risk data and the intensive calculation [1].

A digital twin (DT) is a way to replace a subjective and periodic assessment with continuously synchronized evidence. By definition a DT is a virtual representation of a physical system which is linked to it by means of twoway data passing and therefore the virtual state is

updated from the physical system and decisions made virtually are returned to the physical system. The concept was found in the survey of 75 peer-reviewed and grey-literature documents, to have been first mentioned informally in 2002 and to have applications in several areas including manufacturing, aviation and hospital management and precision medicine, and to be made possible by the combined efforts of artificial intelligence, ubiquitous connectivity and big data processing [2].

In the built environment, twins have evolved from geometric building information modelling (BIM) to semantically rich representations. A research agenda on the semantic construction digital twin was presented, which highlighted that BIM is not equipped with live data, interoperability and reasoning to truly enable a digital twin and that semantic web technologies were required to connect diverse construction data to sensing and simulation [3]. That agenda is asset and project centric, and doesn't address much on the portfolio level, where resources and risks are shared.

A square matrix with information or resource flows between elements in the off diagonals has been used for a long time to represent cross-project dependencies: this is called the design structure matrix (DSM). A basic study identified four different types of DSMs: component-based, team-based, activity-based, and parameter-based, and demonstrated how clustering and sequencing algorithms revealed integration issues and iteration loops [4]. These are, however, usually manually generated and analysed on an ad-hoc basis, as opposed to the continual updating with operational data.

The twin principles are extended from physical assets to organisations to provide the missing link. Issues were identified during the architectural analysis of the digital twin of the organization (DTO) that included concerns in modelling business processes, acquiring data from enterprise systems, and separating descriptive, predictive and prescriptive functions [5]. The present review turns to three questions: What concepts and methods from twin, portfolio and AI research can be integrated into a portfolio digital twin; How can capacity, dependency and risk functions be represented; and What are the barriers to adoption?

LITERATURE REVIEW

2.1 Digital Twin Foundations and Synchronization

The core enabling technologies for twins reviewed are the ones from manufacturing, healthcare and smart cities, and the Industrial Internet of Things (IIoT), with data analytics and AI as the key enablers [6]. The same review differentiated twins from simulations by the presence of automated, real-time data-flow, and as open challenges included data quality, latency, security, standardization and infrastructure cost. Each of these challenges re-emerges in the portfolio level, where data are no longer collected from sensors but from a variety of enterprise systems.

The original formulation included a physical product, a virtual product and the data and information flows linking the two and separated them from the digital twin instance [7]. The central role was to reduce the unwanted and unpredictable emergent behaviour in complex systems by exploring them virtually before they materialize. Indeed, this is often the case with portfolio failures that is, the failure is emergent as the result of a model f being propagated by a set of decisions u_t while the observations y_t are corrected by the gain K_t whenever they differ from the predicted observation h(xˆ_t).

$$\hat{x}_{t+1} = f(\hat{x}_t, u_t) + K_t[y_t - h(\hat{x}_t)] \quad (2)$$

2.2 Capacity and Resource Modelling

The resource-constrained project scheduling problem (RCPSP) and its extensions are formal ways of posing capacity questions. RCPSP variants were surveyed and generalized precedence relations, multiple execution modes, time-varying resource availability, multi-project settings, and alternative objectives, like net present value and robustness, were captured [8]. The base line in the equations If S_j is the start time of activity j, d_i its duration, E the precedence set, A(t) the set of activities running at time t, r_jk the resource k requirement for activity j, and R_k its capacity, then (3) and (4) minimizes the makespan subject to precedence and capacity constraints. A capacity twin would keep tracking the utilization ratio ϱ_k (t) as defined in Eq. (5) all the time.

$$\min S_{n+1}, \ \text{s.t.} S_j \geq S_i + d_i \ \forall (i,j) \in E \tag{3}$$

$$\sum_{j \in A(t)} r_{jk} \leq R_k \ \forall k, t \tag{4}$$

$$\rho_k(t) = \frac{\sum_{j \in A(t)} r_{jk}}{R_k} \tag{5}$$

A thematic analysis of 92 twin publications resulted in a list of 13 characteristics of the concept of a twin, including the physical and virtual entities, the environment, the state, metrology, twinning and twinning rate, as well as identified 7 gaps in knowledge, such as the level of fidelity, data ownership, integration of virtual entities [9]. In the context of capacity management, the twinning rate is crucial: in the context of a dynamic model, resource states are changing daily as assignments, absences and approvals are added or removed, and a portfolio twin that is updated only monthly at reporting cycles would be considered a static model. The following Table 2 highlights the defining characteristics presented in the main twin reviews.

Table 1. Defining Characteristics of Digital Twins Reported in Major Reviews

Review	Evidence base	Key characterization	Implication for portfolio twins
[2]	75 documents	Definitions, characteristics and domains (manufacturing, aviation, healthcare)	Socio-technical design and lifecycle view required
[6]	Categorical review	IIoT, data analytics and AI as enablers; twin distinguished from simulation	Automated real-time data flow defines the twin
[7]	Conceptual	Physical entity, virtual entity and connection; prototype versus instance	Emergent cross-project behaviour as target
[9]	92 publications	13 characteristics and seven knowledge gaps	Twinning rate and fidelity must be specified
[10]	Categorical review	DM, DS and DT by data-flow automation; DS 35%, DM 28%	Most portfolio tools sit at DM level
[11]	240 publications	Concepts, technologies and applications by lifecycle phase	Modelling, fusion, interaction and service layers
[12]	State-of-the-art review	Key components, development and industrial applications	Industrial maturity as a benchmark

Source: Synthesized from the cited reviews.

2.3 Dependencies and Strategic Alignment

Empirical studies of project interdependencies found that visual tools such as network maps and matrixes help with making decisions in the portfolio when accompanied by a culture of collaboration and appropriate processes [13]. The DSM is transformed into a weighted, continuously updated graph when it is in twin form. In Eq. (6) the propagated exposure vector p is given by the stand-alone exposure vector s, the weighted dependency matrix D and an attenuation factor α, which is assumed to be less than the inverse of the spectral radius of D, in order to account for indirect effects through chains of any length. In the illustrative example of eight projects in Figure 3, aggregate exposure goes up by about 55% (from 0.90 to 1.39) and the exposure of the most downstream project increases by over 200% (from 0.05 to 0.12).

$$p = (I - \alpha D)^{-1} s = \sum_{m=0}^{\infty} \alpha^m D^m s \quad (6)$$

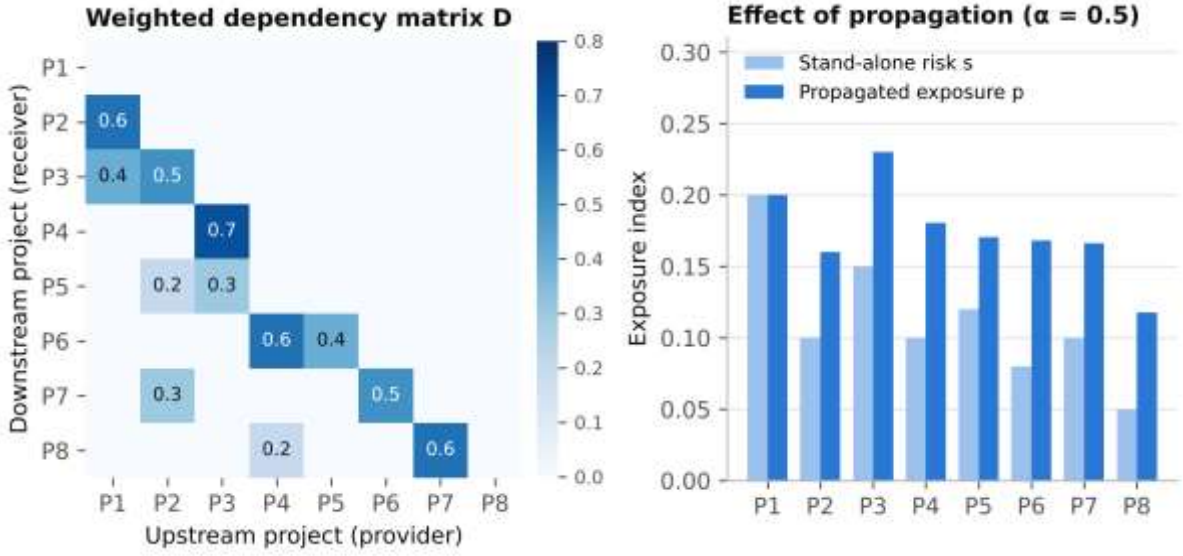


Figure 1. Weighted Dependency Matrix and Propagated Exposure for an Illustrative Eight-Project Portfolio

Note: Illustrative values computed with Eq. (6).

Value of early portfolio decisions is also dependent on dependencies. A survey of 175 firms confirmed a strong positive relationship between front-end success and project portfolio success, and showed that the effect becomes stronger for larger portfolios, for portfolios with more interdependency among projects and for firms with a strategic orientation toward riskiness [14].

The strategic alignment is another dynamic quantity. The study of 182 firms revealed that deliberate and emergent strategies both have positive effects on the success of the portfolio, and that the two types of strategies are complementary, as well as strategic control in the portfolio supporting both, and the strategic control of both strategies being less relevant in more turbulent environments [15]. A practical way to identify strategic patterns that are emerging before they show up in periodic reviews is to be able to continuously sense project-level signals, which is a native function of a twin.

2.4 Integration Levels and Analytics

A review of manufacturing twins categorized it as digital model (DM), which was manual data transfer both ways, digital shadow (DS), which was an automatic physical to the virtual flow only, and digital twin (DT), which was an automatic flow of data in both directions. The proportion

of publications classified as digital shadows (35%) and digital models (28%) was the highest, while the proportion of full twins was low. Table 3 extends this classification to the portfolio functions and suggests that the majority of current portfolio tools will fit into the DM classification.

Table 2. Twin Integration Levels Applied to Portfolio Functions

Level	Data flow (P→V / V→P)	Capacity	Dependency	Risk
Digital model	Manual / manual	Spreadsheet resource plans updated at review cycles	Hand-drawn maps or static DSM	Periodic risk register
Digital shadow	Automatic / manual	Live utilization from timesheets and ERP	Graph refreshed from schedule links	Automated risk indicators and alerts
Digital twin	Automatic / automatic	Reallocation recommendations executed after approval	Propagated impact with re-sequencing	Covariance-aware exposure with triggered mitigation

Note: P = physical portfolio; V = virtual portfolio. Integration levels adapted from [15].

A survey of 240 academic papers was performed and organized the papers into two categories: concepts, technologies and industrial applications by the lifecycle phase, and highlighted modelling, data fusion, interaction and service as the main technical skills [11]. The data layer, model layer and service layer of the architecture in Section 4 have the corresponding capabilities.

Operational anomaly detection is an example of how the analytic layer is used. Using a data structure, the extended Industry Foundation Classes (IFC), a twin based system for building asset monitoring extracted monitoring data, and applied Bayesian change point detection to distinguish load-driven changes from contextual anomalies in centrifugal pumps of a heating, ventilation and air-conditioning system [16]. Portfolios follow similar rules: burn rates, earned value indices and staffing levels fluctuate in response to legitimate demand; deviations from the expected must be adjusted to the context of the portfolio and the deviations should be considered legitimate enough to trigger escalation.

METHODS

Based on the research in multi-objective portfolio selection, the portfolio decision problem was defined as selecting a project set that is able to maximize multiple conflicting objectives within a multi-period resource constraint, where there is interdependency between projects and the potential to transfer unused resources from one period to another [17]. This framing was formalized into three lenses of the review – capacity, dependency and risk – as shown in Eq. (1). In Eq. (1), x_i is a binary decision variable for project i, z_q represents the q-th objective and c_it and B_t are the resources used by project i in period t and the capacity available in period t, respectively. The corpus

consists of 30 peer-reviewed articles from the period from 2001 to 2024, which are categorized into six thematic streams as shown in Table 1 and Figure 1.

$$\max Z(x) = \left[z_1(x), z_2(x), \ldots, z_Q(x)\right], \ \text{s.t.} \sum_{i=1}^{n} c_{it} x_i \leq B_t \ \forall t, \ x_i \in \{0,1\} \quad (1)$$

Table 3. Distribution of the Reviewed Corpus by Thematic Stream

Thematic stream	Sources	n	Share (%)	Period
Digital twin foundations	[2], [8], [9], [11], [15], [16], [23], [26]	8	26.7	2017–2021
Built-environment twins	[3], [17], [24]	3	10.0	2020
Organizational twins	[5], [18], [21]	3	10.0	2020–2024
Portfolio and risk governance	[6], [12], [13], [14], [19], [27], [28], [30]	8	26.7	2010–2019
AI for project management	[1], [7], [20], [25], [29]	5	16.7	2016–2023
Planning and dependency models	[4], [10], [22]	3	10.0	2001–2019
Total		30	100.0	2001–2024

Source: Compiled from the reviewed literature.

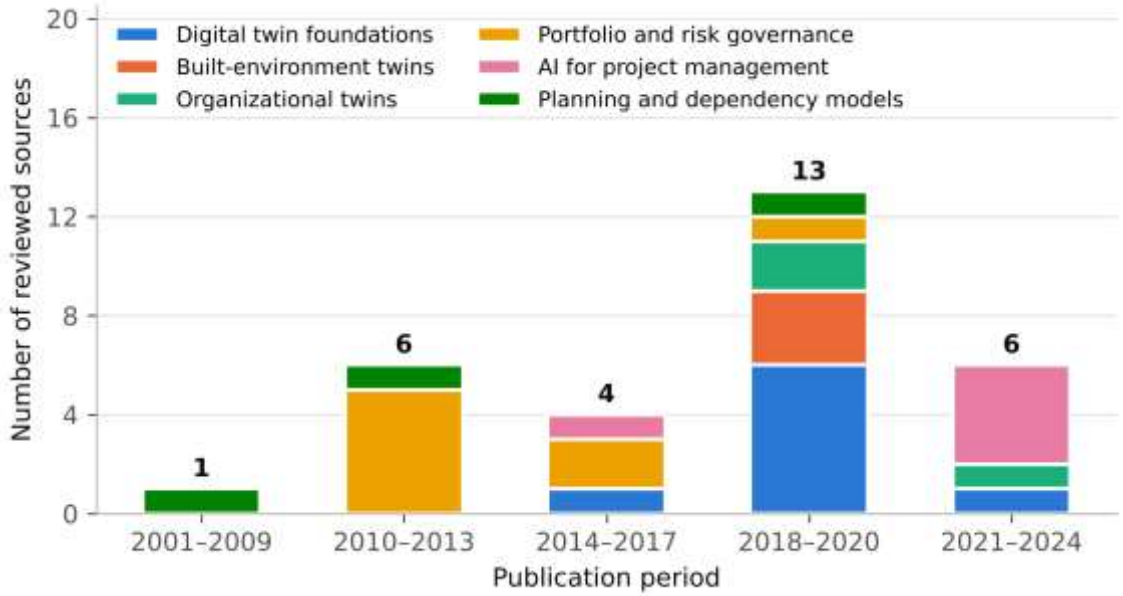


Figure 2. Distribution of the Reviewed Sources by Publication Period and Thematic Stream

Source: Compiled from the reviewed literature.

Every source was assigned a code for the function it provides, the level of twin integration assumed by the source and the AI technique it uses. The coding frame was matched with the ten knowledge areas of the Project Management Body of Knowledge (PMBOK Guide) [6] which was operationalized by an expert study through 49 processes and a 53-item questionnaire to estimate the near-future impact of AI on project management [18]. Schedule, cost and risk management were perceived to be the most impacted areas which is aligned with the focus on capacity, dependency and risk in this synthesis. The response profile for integration management is similar to that of

portfolio coordination with 37% of respondents predicting a high or very high impact, and is reproduced in Figure 2.

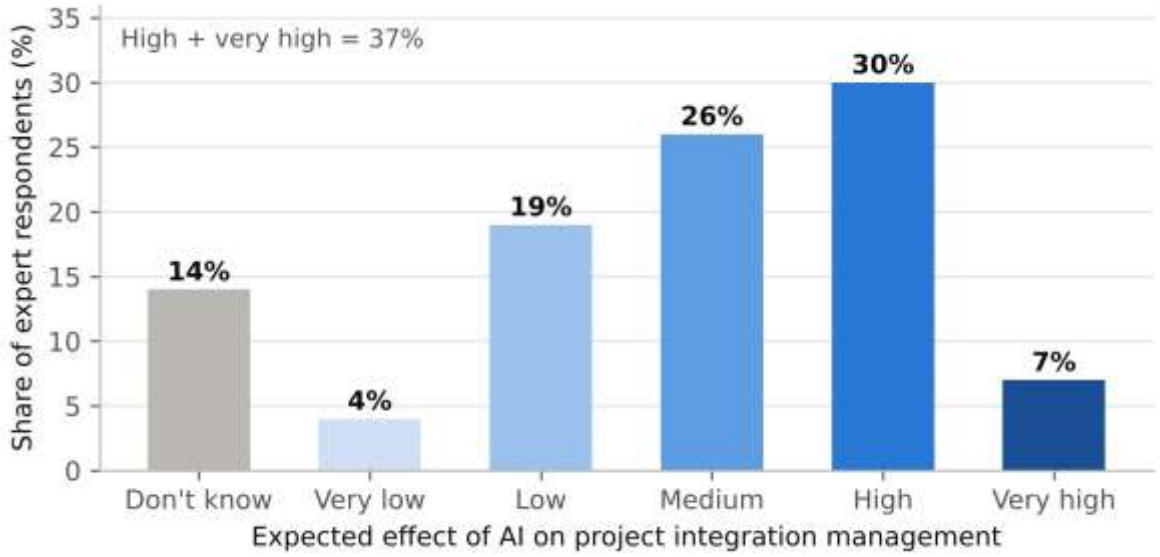


Figure 3. Expert Expectations of the Effect of AI on Project Integration Management

Source: Response distribution reported in [7].

RESULTS AND DISCUSSION

4.1 Reference Architecture for an Organizational Portfolio Twin

The concept of digital twins of organizations states that digital twins change the way of organizing, as processes, routines and their variations become visible and can be modified with the help of data [19] and so can be redesigned continuously instead of episodically. A portfolio twin is a particular kind of DTO, in which the object of representation is a collection of projects shared and tied together by commitments.

But there's a difference between the rational decision model and portfolio practice. We found four assumptions in the empirical research that do not apply to "real life" in a manner that matches normative portfolio management, and found that portfolio management is a process of negotiation, sensemaking and adaptation in a particular organizational context [20]. A portfolio twin, then, should be seen as a moving, evolving evidence base to facilitate negotiation, not as a decision-making tool.

The AI services required by the twin are available in adjacent fields. To identify the most prevalent directions, a scientometric and qualitative study of 4473 articles published between 1997 and 2020 in construction engineering and management journals revealed six directions: knowledge representation and reasoning, information fusion, computer vision, natural language processing, intelligent optimization and process mining, and named digital twins [21]. Every topic relates to a different portfolio twin service, ranging from risk extraction in status reports using natural language processing, to process mining and reconstructing actual workflows.

Guidance on building organizational twins emphasizes experimentation, as changes in structure and operation can be done virtually through experimentation before resources are "spent" [22]. Figure 4 summarizes these findings into a five-layer reference architecture, where the data of

the physical portfolio is synchronized (L2) with the core capacity, dependency and risk models (L3), analysed by AI services (L4), and acted on by governed decisions (L5) that are fed back to the physical portfolio.

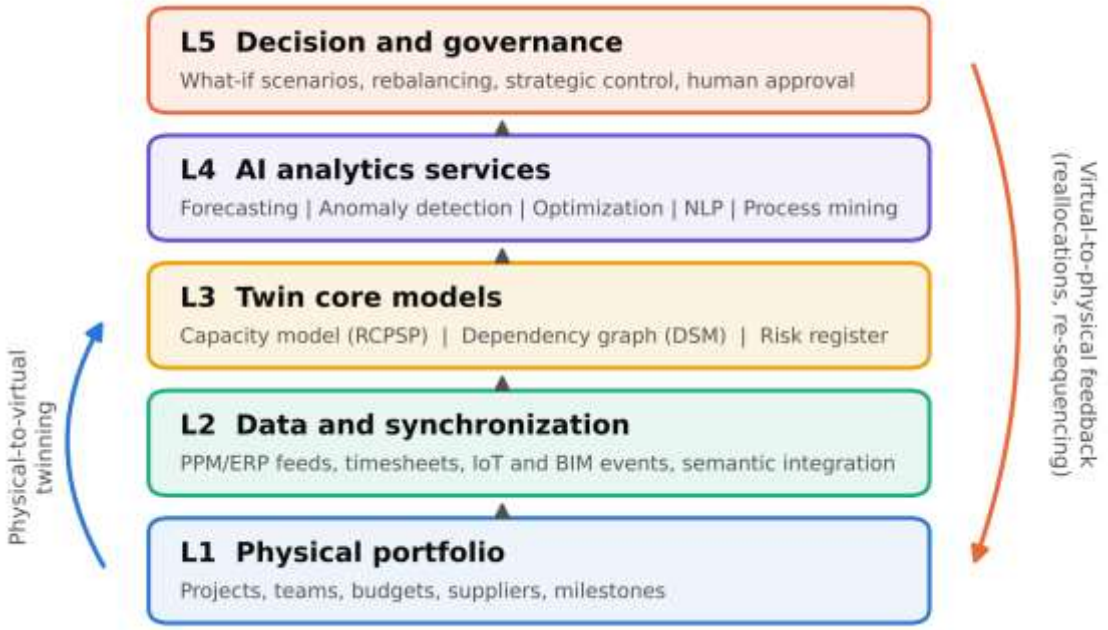


Figure 4. Five-Layer Reference Architecture of the AI-Augmented Portfolio Digital Twin
Source: Synthesized from [5], [16], [18], [21] and [22].

Eight common decision problems were identified as being recurrent in Planning and Control: project representation, scheduling, resource allocation, risk analysis, performance evaluation, forecasting, timing of control points and corrective action, and the transition from scheduling dominated research to stochastic, short term and reactive decision making with the aid of automated data collection [23]. Table 4 lists the techniques of AI present in the corpus based on their twin functions, data requirements and maturity.

Table 4. Comparative Assessment of AI Techniques for Portfolio Twin Functions

Technique	Source	Twin function	Data requirement	Maturity and limitation
Fuzzy hybrid methods and Bayesian belief networks	[1]	Cost-risk assessment and interdependencies	Expert judgement, limited history	Dominant 2008–2018; limited by subjective data
Multiobjective metaheuristic search	[17]	Portfolio selection and rebalancing	Project scores and resource profiles	Handles interdependencies across periods
Expert-assessed AI impact	[18]	Prioritization of knowledge areas	Expert survey (53 items)	Schedule, cost and risk most affected

Bayesian change point detection	[16]	Anomaly detection	Streaming operational data	Validated on HVAC pumps; portfolio transfer untested
Knowledge representation, NLP and process mining	[21]	Data fusion and workflow reconstruction	Documents and event logs	Six active topics in 4,473 articles
Supervised AI forecasters (five methods)	[24]	Duration forecasting	Large, topologically diverse project sets	Outperform EVM/ES when training resembles target

Note: EVM/ES = earned value management and earned schedule; HVAC = heating, ventilation and air conditioning.

4.2 Risk Intelligence and Closed-Loop Control

A combination of physics-based models and data-driven models was highlighted as an important aspect of twin value, as the one will complement the weaknesses of the other, and hybrid analysis and modelling were identified as an enabler, along with big data infrastructure, real-time communication and uncertainty quantification [25]. The very first-principles part of portfolios is the scheduling and dependency logic of Eqs. Components (3) to (6) estimate durations, productivity and risk likelihoods.

Twins have been put forward as information systems to support closed-loop production planning and control, in which the monitored status is compared to plans, and deviations initiate replanning cycles [26]. The same loop works, but on a slower weekly to monthly time frame, at the Portfolio level.

A systematic review of AI in project management identified the use of AI as a way to reach project goals more efficiently, which aligned with the human-centric approach that is a core part of Industry 5.0, and categorized the use of AI in project management processes [27].

A state-of-the-art review of industrial twins discussed the essential elements of a twin, its development trajectory and its main application areas and defined the twin as one of the most promising enabling technologies for smart manufacturing [28] . Table 5 compares the differences between industrial, built-environment and portfolio twins, and Figure 5 shows the size of the evidence base, which is large for both twin and AI research, but with a solid basis on surveys of firm-level for portfolio management.

Table 5. Comparison of Industrial, Built-Environment and Portfolio Twins

Dimension	Industrial twin	Built-environment twin	Portfolio twin
Physical entity	Machine, line or product	Building, infrastructure asset or site	Projects, shared resources and commitments

Primary data sources	Sensors, IIoT and control systems	BIM, IFC, IoT and site monitoring	PPM, ERP, timesheets, schedules and status reports
Indicative twinning rate	Seconds to minutes	Minutes to days	Days to weeks
Dominant models	Physics-based and machine learning	Semantic and geometric models	Scheduling, DSM and stochastic risk models
Integration maturity	DS (35%) and DM (28%) dominate	Emerging closed loops	Mostly digital model
Key decisions	Control and maintenance	Operation and production control	Selection, allocation and sequencing

Source: Synthesized from [3], [15], [17], [24] and [26]; twinning rates are indicative.

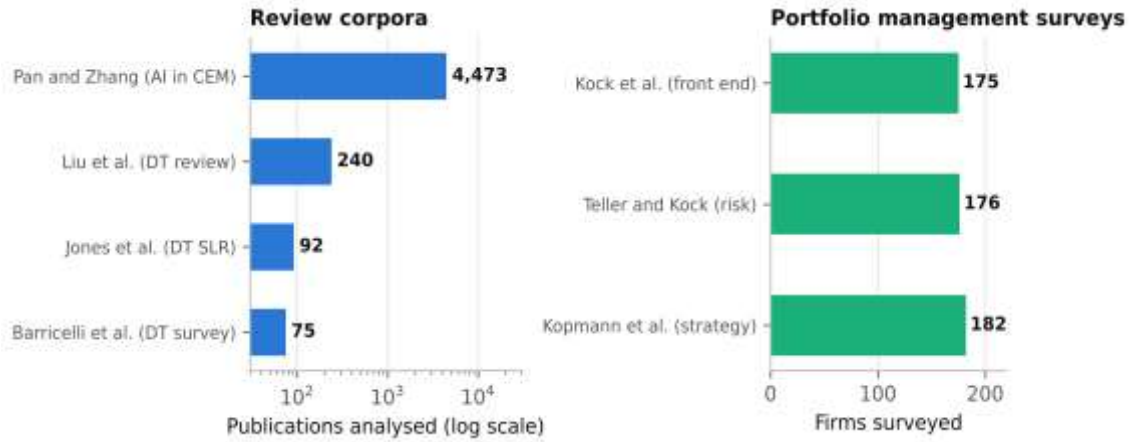


Figure 5. Size of the Evidence Base in Twin, AI and Portfolio Management Research

Source: Data reported in [2], [11], [13], [14], [16], [20] and [27].

Portfolio risk management is measurable and has an impact on the outcomes. A survey of 176 companies revealed that portfolio risk identification, formalization of the portfolio risk management process and a risk management culture leads to higher risk transparency and the capacity to deal with risks, thus enhancing the portfolio success [29]. The measure of portfolio exposure in Eq. (7) is based on the dependability graph, and not on the assumption of independence, since it uses the twin estimates of the covariance of deviations from the outcomes of projects, σ_ij, and the weights of the projects, w_i. The illustrative Monte Carlo simulation in Figure 6 demonstrates that incorporating the finish-to-start coupling can increase the P80 completion time for the portfolio from 17.1 to 27.0 months or approximately 58%.

$$\sigma_P^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \quad (7)$$

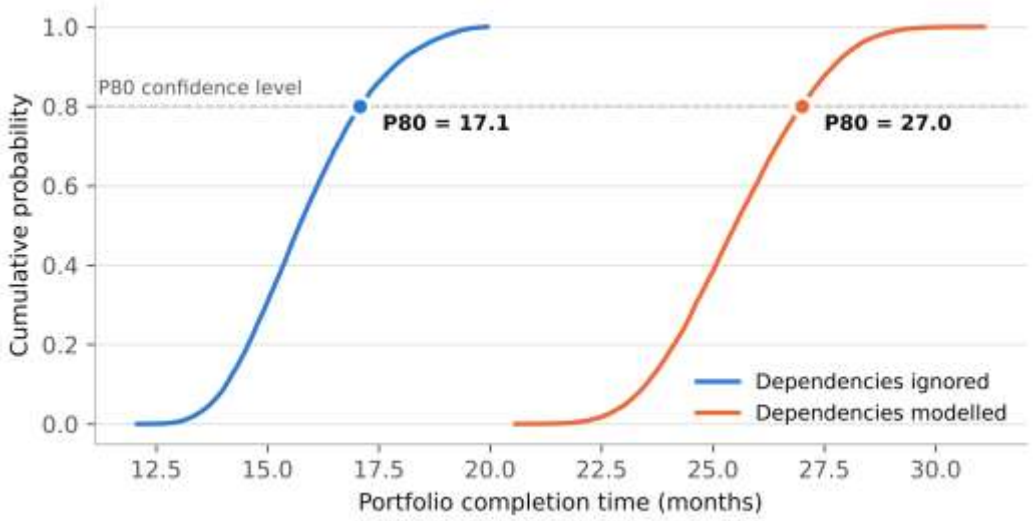


Figure 6. Portfolio Completion Time With and Without Dependency Coupling

Note: Illustrative Monte Carlo simulation, 20,000 iterations, triangular activity durations.

Any formalization is also dependent on complexity. Individual project management and portfolio management were both found to have a positive impact on portfolio success, but their combined impact was greater than the sum of the two, and the impact was stronger in more complex portfolios with size and interdependency [30]. Common data definitions and automated controls reduce the administrative burden that can deter formalization, via a twin.

4.3 Forecasting Accuracy, Value and Adoption Challenges

The evidence of forecasting is based on a measure of optimism. The best performance results for project duration forecasting were achieved by five AI approaches, using Monte Carlo simulation, principal component analysis and cross validation; these five approaches performed best when training and test projects were similar and did well in early and mid-stage forecasting, however a robustness experiment demonstrated that performance degraded as the set of training and test projects grew more different. [24] The quality of forecasts should thus be continuously monitored, perhaps using the mean absolute percentage error (MAPE) in Eq. (8) where the models are recalibrated if the portfolio composition changes, T_h is the period of the project h and T ˆ_h is the period of the target project h among H projects completed up to date.

$$\text{MAPE} = \frac{100}{H}\sum_{h=1}^{H}\frac{|T_h - \hat{T}_h|}{T_h} \quad (8)$$

The last one is value, and value is not inherent in the technology. An interview study showed that the concept of project risk management value is subjective and situational, as stakeholders' perception of its importance in a project depends on their perception of what is important about the project, and challenged the position of the universal ideal of project risk management value in the literature [30]. A Portfolio twin thus needs to be set up with stakeholders it will serve, and the outputs of the twin should be humanly understandable, auditable, and approved. Table 6 provides an overview of the main challenges, their implications, and directions of mitigation supported by the evidence reviewed.

Table 6. Adoption Challenges and Mitigation Directions

Challenge	Evidence	Implication	Mitigation direction
Data integration and semantics	[3], [8]	Heterogeneous enterprise data impede synchronization	Semantic data layer and common definitions
Fidelity and twinning rate	[11]	Stale states mislead capacity decisions	Specify twinning rate per function
Model transferability	[29]	Forecasts degrade when portfolio composition drifts	MAPE monitoring and recalibration
Subjective risk data	[1]	Bias in exposure estimates	Bayesian updating with observed data
Practice and negotiation	[19], [30]	Automated advice may be rejected	Human approval, explainability and co-design
Formalization cost	[28]	Administrative burden of formal processes	Embed formalization in automated controls

Source: Synthesized from the reviewed literature.

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CONCLUSION

This systematic review integrated evidence from twin engineering and portfolio management and AI research, to provide a definition of an AI-augmented project portfolio digital twin for dynamic capacity, dependency and risk management. Three findings emerge. On the conceptual side, first, twin technology is consolidated, and there are 13 defining characteristics and a definite separation between models, shadows and twins, while portfolio applications are still at the level of the models and shadows. Secondly, portfolio research has shown that front-end quality, strategic control, formalization and portfolio risk management are all key success factors, and that all of these are supported by continuous and data-driven visibility. Third, existing formal and AI building blocks are available: dependencies from a resource-constrained schedule, dependency propagation based on DSMs and covariance-based exposure and machine learning forecasts can be used within a proposed five-layer framework, and illustrative calculation results demonstrate that dependency neglect seriously underestimates the exposure and completion risk. Further research should confirm the architecture through the use of real longitudinal portfolio data, confirm fidelity and twinning-rate requirements for organizational data, and explore explainable human-governed decision support in real portfolio governance.

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