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Advancing resilience in infrastructure projects through machine learning-driven models

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ABSTRACT

Traditional risk management enhances infrastructure utility but remains limited in addressing complexity and uncertainty. This has shifted attention towards resilience, particularly the readiness dimension, to improve early threat detection and prevention. Machine Learning (ML) offers opportunities to advance resilience modelling, yet empirically validated ML-enabled approaches, especially those using neural networks, are scarce, restricting accuracy, reliability, and applicability. This study develops a neural network-enabled resilience model optimized for training efficiency and predictive performance. By incorporating established feature importance techniques, the model improves accuracy, interpretability, and the identification of influential factors. The findings extend resilience typologies by ranking factor importance in critical infrastructure, highlighting '*Operational resilience*' as the most significant determinant of project success. Practically, the model provides managers with clearer insights for decision-making, supporting earlier threat recognition and stronger disruption detection. The framework is adaptable across resilience contexts with appropriate industry-or platform-specific modifications.

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1. Introduction

In recent years, global demand has surged for complex, multi-stakeholder, and technologically advanced projects that deliver not only individual critical infrastructure assets and platforms (Roehrich et al. 2024; Zhang et al. 2024), but also systems that are highly interdependent and connected (Grafius, Varga, and Jude 2020; Mao and Li 2018). Critical infrastructure is defined as '… *an asset, system or part thereof […] which is essential for the maintenance of vital societal functions, health, safety, security, economic or social well-being of people, and the disruption or destruction of which would have a significant impact […] as a result of the failure to maintain those functions*' (European Council 2008). These assets may be either physical or virtual (Sarker 2024) and can be privately owned or publicly operated (Alkhaleel 2024; Dick et al. 2019).

Critical infrastructure relies on a global network of interconnected physical and digital interconnected systems to manage functions such as power distribution, water management, security, and energy efficiency. Examples include airports, logistics hubs, data centres, and power grids, which are particularly vulnerable during the transition from project completion to operational handover (Al-Mazrouie et al. 2021; de Almeida Rodrigues et al. 2024a; Zhang et al. 2024).

These systems are increasingly interdependent, amplifying exposure to risks that often transcend organizational and national boundaries (Al-Mhdawi et al. 2025; Chopra and Khanna 2015; Kumar et al. 2021; Liu, Ferrario, and Zio 2017; Liu et al. 2022; Milanović and Zhu 2017). Disruptions can escalate rapidly and disproportionately (Morkan et al. 2023; Nachbagauer and Schirl-Boeck 2019), causing cascading failures that compromise both individual assets and broader networks (He et al. 2024; Hoff et al. 2025; Li et al. 2024; Sarker et al. 2024), with severe and far-reaching consequences (Zio 2016). The operations and project management literature underscores that unforeseen disruptive events serve as major risks to project success (de Almeida Rodrigues et al. 2024a; Franke et al. 2022; Usher et al. 2025; Yao et al. 2025). Disruption is defined by Alderson, Brown, and Carlyle (2015) as '… *the loss of one or more system components*' (654).

A notable case occurred on 21 March 2025, when a fire at a power substation forced Heathrow Airport into a 24-hour shutdown, cancelling over 1,300 flights and affecting more

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than 145,000 passengers. The disruption paralyzed Europe's largest airport and caused an estimated £4.8 million loss in UK tourism revenue (Matchett 2025). This followed the costly 2008 Terminal 5 opening, which incurred losses of £4.9 billion. Such events highlight the critical need for resilience-focused strategies to manage complex infrastructure systems.

To safeguard operational integrity and mitigate threats to the stability of critical infrastructure, scholars have placed significant emphasis on risk management (de Almeida Rodrigues et al. 2024a, 2024b; Rød et al. 2020). Traditional approaches to risk management have included: (i) risk-informed strategies focused on avoidance, reduction, transfer, or retention; (ii) precautionary strategies aimed at containment, system strengthening, and adaptation; and (iii) uncertainty reduction (Aven 2016; Goessling-Reisemann and Thier 2019).

However, a major challenge currently facing many infrastructure assets and platforms is the evolving nature of risks, which has created significant difficulties for infrastructure project managers, resilience professionals, and ORAT (i.e. *Operations Readiness, Activation, and Transition*) practitioners. Some of these challenges have led to sudden and unexpected disruptions (Usher et al. 2025).

Emerging threats such as terrorism, pandemics, cyberattacks, and climate change were far less prominent a decade ago but have become increasingly dynamic, highlighting limitations in traditional risk management. A key issue is that much of the literature overlooks the constraints of compliance-driven, internally focused processes that rely on static risk listings and registers. Even proactive approaches often lack the *a priori* evidence needed for reliable prediction, limiting their practical utility (Marshall et al. 2019).

In response, several scholars advocate '*resilience*' as a more robust framework for managing evolving infrastructure-related risks (Morkan et al. 2023; Nachbagauer and Schirl-Boeck 2019; Naderpajouh et al. 2020). Bhamra, Dani, and Burnard (2011) define resilience as '*… the capability and ability of an element to return to a stable state after a disruption*' (5376). Resilience is generally conceptualized in three interrelated dimensions: (i) '*Readiness*' (ii) '*Response and adaptation*', and (iii) '*Recovery or adjustment*'. This study focuses on the readiness dimension, reflecting consensus in operations (Aladağ, Demirdöğen, and Işık 2023; Al-Mazrouie et al. 2021), project management (Barham and Daim 2020; Radzi et al. 2022; Shenoy and Mahanty 2021; Xue et al. 2023), and organizational studies literature (Drzensky, Egold, and Van Dick 2012; Griffin, Harding, and Learmonth 2017) that early threat detection and prevention, essentially, ahead of schedule '*preparedness*' is a critical precursor to the successful implementation of innovation, whether in the form of new processes, projects, or initiatives.

The emphasis on '*resilience*' and '*readiness*' departs from traditional risk management, which primarily addresses known, static threats (Vairo et al. 2023). Resilience prioritizes adaptive responses to unknown challenges and has gained prominence in both operations management (Bello et al. 2024; Castillo 2023; Han, Chong, and Li 2020) and project management research (Morkan et al. 2023; Nachbagauer and Schirl-Boeck 2019; Rahi, Bourgault, and Robert 2019). Yet, its effectiveness is constrained by system complexity (Alkhaleel 2024; Zio 2016), dynamic and uncertain operational environments (Ouyang 2014), and limited integration of emerging technologies, including Machine Learning (ML). Consequently, current resilience capabilities are insufficient to fully prevent or mitigate failures in critical infrastructure.

Modelling provides a structured approach to understanding, analysing, and predicting complex systems (Bertrand and Fransoo 2002; Choi, Wallace, and Wang 2018; Jeon and Kim 2016; Rolstadås 1993). Widely used in operations and project management, models capture essential aspects of real-world processes (Bertrand and Fransoo 2002; Jeon and Kim 2016; Williams 2003), support decision-making (Bertrand and Fransoo 2002; Hernández, Mula, and Ferriols 2008), and facilitate examination of key variables and interactions, enabling more accurate anticipation of system behaviour and informed decisions.

Resilience models play a vital role in evaluating how infrastructure systems perform under disruptive conditions by examining the key factors that influence readiness, response/adaptation, and recovery/adjustment (Alkhaleel 2024; Ji et al. 2024). These models help analyze the interplay among critical resilience attributes, such as maintainability, reliability, and vulnerability, that collectively determine overall infrastructure resilience. Various modelling approaches can be applied, including data-driven, network-topology-based, and optimization-based methods, as well as those involving simulation or physics-informed ML (Ji et al. 2024).

Previous studies have predominantly focused on leveraging ML to significantly enhance resilience models by improving their accuracy, adaptability, and overall performance (Ghobakhloo et al. 2025; Li et al. 2025; Marcucci et al. 2022). Several studies have specifically examined how resilience can be strengthened through the application of ML approaches (da Mata, Silva, and Fiondella 2023; Wang et al., 2021; Wu and Wang 2023; Zang et al. 2024).

Despite these advancements, there remains a notable gap in empirical research examining the use of ML techniques, particularly neural network-based methods, to improve the resilience of critical infrastructure. This deficiency has limited the precision, reliability, robustness, and practical utility of existing ML-enabled resilience frameworks (da Mata, Silva, and Fiondella 2023; Zang et al. 2024). Consequently, there is an urgent need for field studies to investigate the effective deployment of neural network-based ML approaches to enhance the resilience of critical infrastructure. This imperative is further underscored by the growing complexity of critical infrastructure across multiple dimensions, including physical and digital asset functionality, organizational processes (e.g. project and implementation workflows), human factors (e.g. resource management), and technological aspects (e.g. data volume, dimensionality, and real-time processing requirements).

The distinctive characteristics of critical infrastructure, coupled with the imperative for timely resilience planning, create significant challenges for project managers, resilience practitioners, and ORAT specialists, all of whom require systematic and proactive strategies to anticipate, respond to, adapt to, and recover from disruptive events. Conventional resilience models fall short in this aspect, as they are primarily based on rules defined by expert-defined rules and linear statistical methods. This implies that they are, for instance, more appropriate for isolated, instantaneous disruptions and responses rather than for recurring disruptions over an extended period (Alderson, Brown, and Carlyle 2015; Almaleh 2023; Madni, Erwin, and Sievers 2020).

The problem therefore is that while such models provide useful descriptive and diagnostic insights, they are generally ill-equipped to accommodate the nonlinearity, high dimensionality, and rapidly evolving data environments characteristic of modern critical infrastructure.

In contrast, ML-based models demonstrate superior resilience capabilities by offering data-driven, adaptive, and real-time decision support. Against this backdrop, the present study seeks to develop an empirically validated resilience model that establishes correlations between key resilience factors and project success. To this end, the study harnesses the capacity of neural networks, comprising interconnected processing units, to manage large and complex datasets essential for representing critical infrastructure systems (Larsson and Große 2023; Nirandjan et al. 2022; Sharifi and Goli-Bidgoli 2022) and supporting resilience planning (Abdalla 2025; Biswas et al. 2026; Guo, Lin, and Benitez 2025). Accordingly, neural network-based ML techniques are applied to construct a robust resilience model designed to enhance the operational integrity of critical infrastructure. Of particular significance is the ability of neural networks to generate predictive insights by iteratively adjusting the strength of inter-unit connections (Khan et al. 2018; Samek et al. 2017). Accordingly, the guiding research question is as follows:

RQ: *How can neural network-based ML models be leveraged to strengthen the resilience of critical infrastructure?*

To address the research question, the remainder of the paper is organized as follows. Section 2 explores the resilience concept in greater detail, with particular attention to readiness. Section 3 reviews relevant ML literature. Section 4 outlines the research methodology. Section 5 presents the analysis, conducted using a fully connected feed-forward neural network trained with the *Adam optimiser*. Section 6 reports the results of the analysis across eight *input–output* models. Section 7 discusses the findings, and Section 8 concludes the paper.

The key outcome of this study is the development and implementation of an empirically validated resilience model that identifies correlations between key resilience factors and project success. Model training and performance optimization are achieved through *Hyperparameter optimization* (HPO) using *SEQuential LEarning Curve Training* (SELECT). To enhance accuracy, interpretability, and reliable identification of influential factors, the study incorporates three established Artificial Intelligence (AI) feature importance techniques: *SHapley Additive exPlanations* (SHAP), *Local Interpretable Model-agnostic Explanations* (LIME), and *Permutation Feature Importance* (PERM/PFI). These complementary methods provide diverse and robust insights into feature dependencies, enabling a deeper understanding of the model's decision-making process. Methodological novelty arises from the distinctive integration of three core components: the *input–output* models used to assess feature and factor importance, the approach adopted to ensure optimal model training and performance, and the application of ML feature importance techniques for interpretability.

2. Resilience

2.1. Key concept

Originally conceptualized by Holling (1973) as '… *the ability of ecological systems to absorb changes caused by a disturbance and still persist*' (17), resilience is inherently multidisciplinary and has since been extensively developed across fields including engineering, psychology, and the social sciences (Bhamra, Dani, and Burnard 2011; Hillmann 2021; Phillips and Chao 2024). It is widely regarded as an 'umbrella concept' (Vakilzadeh and Haase 2021), encompassing numerous definitions, factors, and perspectives (Bhamra, Dani, and Burnard 2011; Phillips and Chao 2024; Zhou, Wang, and Yang 2019). Wied, Oehmen, and Welo (2020), for example, identified more than 251 distinct definitions, while Rød et al. (2020) summarized many others. These variations largely depend on context (Bhamra, Dani, and Burnard 2011). Nonetheless, a common core remains: resilience consists of three interrelated dimensions (i) '*readiness*' (ii) '*response and adaptation*', and (iii) '*recovery*' or '*adjustment*' (Alderson, Brown, and Carlyle 2015; Alkhaleel 2024; Bhamra, Dani, and Burnard 2011; Ponomarov and Holcomb 2009).

'*Readiness*' denotes a behavioural and psychological state directed towards early detection and prevention of threats. Defined as '… *the knowledge and capacities required to effectively anticipate, respond to, and recover from the impacts of likely, imminent, or current threats*' (United Nations Office for Disaster Risk Reduction 2017), readiness highlights preparedness through dynamic monitoring to ensure proactive responses (Al-Mazrouie et al. 2021; Wang et al. 2024).

However, resilience extends beyond anticipation. As Pariès (2011) notes, '… *the conditions for resilience cannot be reduced to anticipation*' (6). Accordingly, resilience also involves '*response and adaptation*' (Ten Broeke et al. 2017). Similar to dynamic capabilities (Robson, Ojiako, and Maguire 2024), critical infrastructures must react to threats and adapt to evolving risks to remain viable despite disruption. '*Responses*' are expected to be prompt and targeted, involving absorption, resistance, or recovery. '*Adaptation*' on the other hand, is more long-term, aimed at strengthening systems to meet new risk environments. Without such adaptation, organizations risk repetitive recovery-focused cycles that reinforce dysfunctional development (Burnard and Bhamra 2011). In this dimension, absorptive and adaptive capacities jointly define resilience: '*absorptive capacity*' is evident in redundancy management, while '*adaptive capacity*' emerges through emergency management strategies (Wang et al. 2024).

'*Recovery or adjustment*' involves actions and capabilities to restore performance after disruption (Chowdhury and Quaddus 2016; Kassa et al. 2023; Ponomarov and Holcomb 2009). It is defined as the ability to '*… return to [its] original state or move to a new, more desirable state after being disturbed*' (Christopher and Peck 2004, 2). Increasingly, '*recovery*' is seen less as returning to normalcy and more as transitioning to a stronger state with enhanced capabilities (Dennehy et al. 2021). At this point, emphasis falls on resource distribution for system restoration, with stakeholders playing a pivotal role by coordinating communication and shaping recovery strategies to secure restoration (Wang et al. 2024; Yang et al. 2022).

2.2. Types of resilience

'*Resilience*' is a multi-level construct that manifests at the individual, team, organizational, industry, national, and supranational levels (Scholten, Stevenson, and van Donk 2019). Within this spectrum, '*organisational resilience*' refers to the restorative and transformative responses of organizations when confronted with adversity (Akgün and Keskin 2014; Börekçi et al. 2021; Burnard and Bhamra 2011; Koh et al. 2024).

The literature identifies two main perspectives on '*organisational resilience*' (Börekçi et al. 2021; Koh et al. 2024). The first emphasizes the organization's ability to rebound and subsequently reinvent or transform intra- and inter-organizational operations as a strategy for managing disruptions. This aligns with '*operational resilience*' (Essuman, Boso, and Annan 2020; Essuman et al. 2022, 2023; Munoz and Dunbar 2015). The second focuses on building and sustaining relationships, highlighting learning from networks to restore and then reinvent the organization, a perspective associated with '*relational resilience*' (Börekçi et al. 2021; Gerçek and Börekçi 2021).

In the context of this study, '*stakeholder resilience*' is defined as the capacity of individuals or groups with vested interests in critical infrastructure projects to adapt to change, withstand adversity, and sustain their ability to contribute to overall project resilience (Anderson and Guo 2021; Morkan et al. 2023; Naderpajouh et al. 2020; Nguyen et al. 2023).

Superior communication capabilities are critical for information sharing among project stakeholders (Babič, Sinković, and Dolšek 2023; Doerfel et al. 2022; Kim 2021). Continuous sensemaking through communication enhances '*stakeholder resilience*' by enabling early dissemination of risk-related information, dismantling silos, aligning priorities, maintaining situational awareness, and fostering shared understanding of threats (Anderson and Guo 2021; Yang et al. 2022). In contrast, limited communication capacity impedes resilience-building, leaving organizations less responsive and less flexible in orchestrating and reconfiguring resources (Belhadi et al. 2022).

2.3. Prior studies

Numerous studies have highlighted '*resilience*' as a framework for managing evolving infrastructure risks. Some are theoretical (Nachbagauer and Schirl-Boeck 2019; Naderpajouh et al. 2020), while others such as Ulak et al. (2022), Morkan et al. (2023), Scholten et al. (2023), Nickdoost et al. (2024) and Wang et al. (2024), are empirical.

Ulak et al. (2022) introduced a model for evaluating resilience in complex infrastructure networks. Morkan et al. (2023) used semi-structured interviews to examine citizenship behaviour and critical transition in fostering resilience in large-scale projects. Scholten et al. (2023) analyzed supply chain resilience, showing that human factors and maintenance setups critically affect both resilience and costs in essential networks. More recently, Nickdoost et al. (2024) developed a composite index to quantitatively measure infrastructure resilience, incorporating technical, socioeconomic, and geographical factors. Wang et al. (2024) proposed a multi-stage framework for resilience analysis and optimization, enabling continuous trade-offs between resources and resilience goals.

Several studies have explored '*readiness*' as a key dimension of '*resilience*'. Barham and Daim (2020) proposed a hierarchical decision model leveraging lessons from big data projects. Al-Mazrouie et al. (2021) developed a risk-focused readiness framework linking project success to preventing recurrent failures in airport infrastructure. Shenoy and Mahanty (2021) created a stakeholder-oriented readiness framework for megaprojects by integrating 19 critical success factors into a fuzzy logic model. Radzi et al. (2022) surveyed 109 practitioners to identify 18 readiness-related decision criteria in construction projects. Aladağ, Demirdöğen, and Işık (2023) prioritized ORAT activities in airport projects using the Pythagorean Fuzzy Analytical Hierarchy Process (PFAHP). Xue et al. (2023) examined schedule risks in large airport projects, identifying 21 readiness factors.

Al-Mazrouie et al. (2021) provides one of the most comprehensive empirical studies on infrastructure readiness and serves as a foundation for this research. In a United Arab Emirates-based study, they developed a risk-focused readiness framework linking project success to preventing recurrent failures in airport infrastructure. Using a survey of 724 ORAT professionals and Structural Equation Modelling (SEM) via SPSS/AMOS, they identified a four-factor typology: '*Facilities*', '*Organisations*', '*People*', and '*Technology*'. This four-part typology is recast within the broader resilience framework to address disruptions and ensure critical infrastructure success.

'*Facilities*' focus on physical assets, exemplified by the Heathrow Airport shutdown on March 21, 2025, which demonstrated the critical role of infrastructure in supporting operations (Marshall et al. 2020). Prior literature confirms strong links between facility factors and project success (Grimaz, Ruzzene, and Zorzini 2021; Losada, Scaparra, and O'Hanley 2012). '*Organisations*' must adapt and reconfigure routines amid unpredictable disruptions (Marcucci et al. 2022; Scholten, Stevenson, and van Donk 2019). Beyond recovery, performance improvements are pursued post-disruption (Peters et al. 2023; Zhang et al. 2023). Key enablers of organizational resilience include strategic flexibility (Shao and An 2024), organizational memory (Cotta and Salvador 2020), and an adaptive culture (Altay et al. 2018). '*People*' are central to resilience, as adaptability, commitment, and competence sustain operational continuity (Bouguerra et al. 2024; Scholten, Stevenson, and van Donk 2019). Psychological strengths enable flexibility and improvization in dynamic settings (Youssef and Luthans 2007), translating organizational resilience into effective project execution (Sutcliffe and Vogus 2003). '*Technology*' supports crisis management and operational continuity (Gupta et al. 2024; Lee et al. 2019), reinforcing social structures in uncertain environments (Mark and Semaan 2008). Key areas include daily operations, asset optimization, and ML applications (Lee et al. 2019). The Heathrow incident highlighted the need for robust technological contingency planning and effective human-technology integration.

Despite extensive research on resilience and readiness, leveraging these concepts remains challenging due to complexity, uncertainty, and evolving infrastructure risks. ML offers promising opportunities to strengthen infrastructure resilience and readiness.

3. Machine learning (ML)

3.1. Definition and key concept

Defined as '*… a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other types of decision making under uncertainty*' (Murphy 2018, 1), machine learning (ML) is a subfield of Artificial Intelligence (AI) (Brynjolfsson and Mitchell 2017; McKinsey & Company 2024a, 2024b; Wang, Skeete, and Owusu 2022; Wang et al. 2022). While AI broadly encompasses technologies enabling machines to exhibit human-like intelligence, ML equips systems to process structured and unstructured data using techniques such as natural language processing (NLP) and neural networks (NN). These methods allow machines to achieve 'intelligence', make decisions, and perform complex predictive tasks autonomously (Duan, Edwards, and Dwivedi 2019; Jordan and Mitchell 2015). ML is data-intensive, relying on large datasets to support automation in complex decision-making processes (Lolli et al. 2019).

By leveraging computational tools, large datasets, and image analysis trained on empirical observations (Barber 2012; Jackson 1988; James et al. 2000), ML algorithms can analyze complex, nonlinear relationships with high accuracy (Hammesfahr and Spott 2023). Unlike traditional statistical methods, ML does not impose restrictive assumptions on process parameters. Its computational capabilities uncover previously unrecognized patterns and establish precise correlations between *input* and *output* variables. Continuous learning from data enables ML systems to improve performance over time without explicit human intervention (Brynjolfsson and McAfee 2017; McKinsey & Company 2024b).

ML capabilities are implemented through advanced algorithms such as neural networks, which emulate the human brain's approach to data analysis. '*Neural networks*' consist of interconnected nodes organized into layers, with each node communicating via weighted connections (Choi et al. 2020). This structure allows learning from past experiences, enabling tasks ranging from simple pattern recognition to complex operations such as energy demand forecasting (Jin et al. 2022; Olu-Ajayi et al. 2022). Neural networks excel at handling missing data and compensating for system faults, enhancing performance in dynamic and uncertain environments (Khan, Wang, and Liu 2022; Usuga Cadavid et al. 2020). These attributes make them powerful tools for decision-making in highly complex, disruptive, and uncertain contexts (Kohl and Miikkulainen 2009; Kosasih and Brintrup 2022; Thuy and Benoit 2024).

3.2. ML For resilience

ML as a pattern-recognition technique, offers substantial potential for optimizing resilience processes. Understanding the behaviour of infrastructure assets is critical for designing highly resilient systems, with factors such as facilities, organization, people, and technology influencing resilience properties (Al-Mazrouie et al. 2021). Identifying correlations between resilience factors and project success is essential for characterizing the resilience of critical infrastructure assets. ML models are particularly effective at managing the intrinsic complexity of data associated with infrastructure resilience.

Global interest in applying ML (Alkhaleel 2024; Almaleh and Tipper 2021; Buxton, Uma, and King 2010; Elvas et al. 2021; Wang et al. 2021; Wu and Wang 2023), and specifically neural network models (da Mata, Silva, and Fiondella 2023; Dick et al. 2019; Ulak et al. 2022; Zang et al. 2024), to resilience optimization has increased significantly. ML models demonstrate potential across multiple domains to enhance resilience, including: (i) dynamic risk representation and capacity assessment (ii) predictive modelling (iii) real-time monitoring and deviation detection (iv) early warning signal identification, and (v) optimal, adaptive decision support. Additional benefits encompass (vi) continuous learning (vii) scenario simulation and stress testing (viii) optimization of recovery strategies, and (ix) integration of diverse data sources.

3.3. Prior studies; ML for infrastructure resilience

Recent studies have increasingly explored ML to enhance the resilience of critical infrastructure across its various dimensions. In the readiness dimension, Buxton, Uma, and King (2010) applied Bayesian Belief Networks (BBNs), a probabilistic ML technique, to simulate system readiness through interdependence mapping and conditional probability tables. Similarly, Elvas et al. (2021) developed an ML-based resilience system to improve risk assessment by detecting patterns in textual and spatial datasets.

Almaleh and Tipper (2021) proposed a network indicator–ML model to strengthen readiness by evaluating key infrastructure nodes using four measures: community, criticality, interdependency, and centrality. Wang et al. (2021)

introduced a deep learning and network theory framework to assess 'vulnerability' (i.e. '*susceptibility to harm*' - see Adger 2000), across functional characteristics, recovery strategies, and failure scenarios. Cassottana et al. (2022) addressed large-scale disruptions via a two-stage ML approach: the *InfraRisk* simulation model generated disruption and recovery scenarios, which then trained four ML models to predict resilience levels and identify contributing factors.

Wu and Wang (2023) presented a generative design framework using advanced graph learning, including a design generator based on an unsupervised *Graph variational autoenc*oder (GVAE) to extract system features and create performance-compliant designs. A performance estimator, using a *Semi-supervised graph convolutional network* (GCN), facilitated rapid prediction and iterative refinement. More recently, Wang et al. (2024) investigated the link between resilience performance and decision-making by proposing a resource allocation framework. Five decision scenarios were formulated, and a *Multi-resilience-objective mixed-integer linear programming* (MROMILP) model optimized resource distribution across various resilience dimensions.

Beyond readiness, ML applications have also been examined in response and adaptation (Ntalampiras, Soupionis, and Giannopoulos 2015; Yuan et al. 2021; Zhou et al. 2020) and in recovery or adjustment dimensions (Aslani and Mohebbi 2024; Balakrishnan, Cassottana, and Verma 2024; Rahimi-Golkhandan, Aslani, and Mohebbi 2022; Ramineni et al. 2023; Yuan et al. 2021), though these are not reviewed here.

3.4. Prior studies; neural networks for infrastructure resilience

Neural networks are among the most widely used ML techniques for enhancing resilience (Kassa et al. 2023). Several recent studies have explored their application to bolster critical infrastructure resilience. Dick et al. (2019) developed a deep convolutional neural network-based approach enabling automatic threat assessment, illustrating the potential of deep learning for infrastructure resilience. Ulak et al. (2022) proposed a holistic model analysing coresilience within networked systems, introducing a *Deep neural network causality-based* (DNNC) method to characterize causal configurations underpinning infrastructure resilience.

da Mata, Silva, and Fiondella (2023) modelled and predicted system performance factors influencing resilience using three neural network types: *Artificial neural networks* (ANNs), *Recurrent neural networks* (RNNs), and *Long short-term memory networks* (LSTM), while also comparing predictive accuracy through *Multiple linear regression with interaction* (MLRI) analysis. Most recently, Zang et al. (2024) introduced a *Temporal decomposition-based dynamic multi-granularity graph neural network* (TD^2MG^2NN) for predictive resilience assessment and developed a composite resilience indicator to capture detailed variations in system resilience. The model's primary innovation lies in its capacity for dynamic updates, enabling real-time evaluation.

3.5. The literature gap

Despite the expanding body of research, a clear gap persists: the literature lacks a comprehensive understanding of how to effectively leverage neural network-based ML models to enhance the resilience and readiness of critical infrastructure. While some ML models, particularly neural network approaches, have been developed for resilience optimization, many rely on post-disruption recovery data or idealized assumptions and trends (da Mata, Silva, and Fiondella 2023; Zang et al. 2024). These limitations undermine confidence in the accuracy, reliability, and practical applicability of existing models. Challenges related to explainability, outcome interpretation, poor-quality training data, and excessive model complexity further compromise model integrity, highlighting the need for field-based research exploring effective neural network applications in infrastructure resilience.

In response, this study conducts a *post-hoc* analysis of critical infrastructure resilience using the dataset from Al-Mazrouie et al. (2021), selected for four key reasons. First, it is among the most comprehensive and relevant datasets, addressing *readiness* (the focus of this study) within critical infrastructure *resilience*, where empirically validated ML models remain limited. The dataset includes well-documented variables and consistent measurement standards, providing a robust foundation. Second, the study aims to develop and validate a generalizable model rather than produce time-sensitive forecasts. The dataset was originally collected to construct a generalized, risk-oriented typology of operations readiness for complex, multi-stakeholder infrastructure projects, making it suitable for this purpose. Third, prior research supports the use of older datasets when the goal is to develop generalizable models and when structural relationships are expected to remain stable (Cheng and Phillips 2014; Kelly, Martin-Peters, and Farber 2024). Using a published dataset also mitigates concerns over data confidentiality while enhancing relevance and theoretical robustness for practitioners and academics (Stahl and Wright 2018). Fourth, the dataset clearly articulates correlations between key readiness factors; '*Facilities*', '*Organisations*', '*People*', and '*Technology*' and '*Project success*', enhancing its reliability and suitability for investigation.

The Al-Mazrouie et al. (2021) dataset thus provides valuable historical context, supporting informed decision-making and resilience improvement in critical infrastructure projects. However, while statistical methods such as *Structural equation modelling* (SEM) using *SPSS/AMOS*, as employed by Al-Mazrouie et al. (2021), offer basic insights into variable significance, they are limited in capturing complex, nonlinear interactions among factors. This limitation is critical in resilience research, where relationships may be subtle yet impactful. To overcome these constraints, this study develops and implements neural network-based ML techniques to construct a comprehensive resilience model capable of detecting correlations between essential resilience factors and project success.

4. Methods

4.1. Outline

A neural network model is applied to conduct a *post-hoc* analysis of the Al-Mazrouie et al. (2021) dataset. To optimize training and model performance, *Hyperparameter optimisation* (HPO) is conducted using the *SEQuential LEarning Curve Training* (SELECT) method, enhancing the predictive capability of the neural network (Smith and Wong 2022). This approach is particularly advantageous, as it systematically addresses the high sensitivity of ML models to hyperparameters, such as learning rate, which can significantly affect performance. Employing SELECT facilitates the efficient identification of optimal hyperparameter combinations, improving model accuracy while reducing computational costs.

4.2. Feature importance techniques

Building on the proposed optimized model, three ML feature importance techniques are applied: *SHapley Additive exPlanations* (SHAP), *Local Interpretable Model-agnostic Explanations* (LIME), and *Permutation Feature Importance* (PERM/PFI). Each technique offers complementary insights into the relationships between *input* variables and *outputs*, providing a robust approach for feature importance analysis (Holzinger et al. 2020).

- SHAP which is grounded in cooperative game theory, assigns an importance value to each feature based on its contribution to model predictions (Lundberg and Lee 2017). By computing Shapley values across the dataset, SHAP quantifies each feature's additive effect on predictions, offering a theoretically grounded, globally consistent explanation that highlights nonlinear relationships and feature interactions. Caution is advised in cases of multicollinearity.
- LIME provides local, model-agnostic interpretations for individual predictions (Biecek and Burzykowski, 2021; Ribeiro, Singh, and Guestrin 2016; Samek et al. 2021). By approximating a complex neural network with a simpler interpretable model in the vicinity of each prediction, LIME clarifies how specific features influence individual *outputs*, enabling localized analysis even when global importance is low.
- PERM/PFI evaluates a feature's impact by measuring changes in model performance when its values are randomly permuted (Altmann et al. 2010; Molnar, 2019). Using *Mean absolute error* (MAE) as the metric in this study, PERM/PFI quantifies each feature's contribution to predictive power by observing performance degradation when its relationship with the target is disrupted.

The combination of SHAP, LIME, and PERM/PFI provides a triangulated understanding of feature relevance. This multi-faceted approach enhances interpretability and model accuracy, identifies consistently important features, and highlights context-dependent influences, enabling a rigorous assessment of factors shaping the resilience of critical infrastructure.

4.3. Additional considerations

The selected model is particularly suitable for the present study compared with alternatives such as LSTM networks, which are typically better suited for sequential or time-series data in infrastructure and logistics contexts. The *Gated Recurrent Unit* (GRU) offers a comparable alternative with greater computational efficiency due to its simpler architecture (Chung et al. 2014). The model employs a hybrid approach, combining a one-dimensional *Convolutional Neural Network* (1D-CNN) with a GRU. This design leverages the CNN's strength in local pattern extraction alongside the GRU's temporal modelling capabilities. By integrating both architectures, the CGRNN model captures complex spatial and temporal dependencies in sequenced datasets, often achieving superior performance compared with standalone models, including LSTM networks (Kanwal et al. 2022; Lin and Nuha, 2022).

4.4. The sub-factors (and their derivation)

The sub-factors and relationships underpinning the ML-enabled resilience model are based on a pre-validated framework developed through a rigorous six-stage process by Al-Mazrouie et al. (2021). This process began with a comprehensive literature review on readiness, identifying nine thematic areas, which were refined through expert judgement into four core factors: '*Facilities readiness*', '*People readiness*', '*Technology readiness*', and '*Organisation readiness*'. A three-phase Delphi study then assessed factor clarity and practical relevance, producing a *Relative Importance Index* (RIX). Subsequently, a survey of 724 project, operations, and ORAT professionals was conducted, with data analyzed using *Confirmatory factor analysis* (CFA) and *Structural equation modelling* (SEM) to validate the factor structure and interrelationships. Al-Mazrouie et al. (2021) also identified 54 sub-factors/items (Table 1), which are recast in the present study as resilience factors. The four core factors comprise the following sub-factors: *Facilities* (7 factors), *Organisation* (24 factors), *People* (8 factors), and *Technology* (15 factors).

4.5. Our research model

Informed by the work of Al-Mazrouie et al. (2021), our research model, presented in Figure 1 below, illustrates the various relationships between resilience sub-factors and project success. In addition to the primary link between '*Operational resilience*' (OpR) and '*Project success*' (PS), there are four Top Level (i.e. first order) features (or factors) in the model together contributing to OpR, these are '*Facilities resilience*' (FR), '*People resilience*' (PR), '*Organisations resilience*' (OR) and '*Technology resilience*' (TR).

Each top-level (first-order) feature is defined by multiple low-level (second-order) features; for example, FR1–FR7 define '*Facilities resilience*' (FR). The model incorporates all 68

Table 1. The resilience factors.

Items	*Resilience*
FR	facilities
PR	people
TR	technology
OR	organization
Items	*Facilities*
FR1	Operational trials and simulation with critical stakeholders.
FR2	Ensure pre-occupancy stocking of all maintenance and operational supplies for all stakeholders.
FR3	New processes and forms will be created and signed off by operations stakeholders.
FR4	Availability of supporting department from contractors and consultant during the initial phase of operations.
FR5	Ensure that all the new fit outs and furniture installation and acceptance are completed.
FR6	Availability of operational and maintenance procedures and processes.
FR7	Availability of all the new operating dependencies and move sequences.
Items	*Organization*
OR1	Operational readiness plan should be part of the project overall planning schedule.
OR2	Documentation of the escalation process and communicating it to all relevant stakeholders of the new facility.
OR3	Establishing joint control room with all the stakeholders for the move sequence and new operations.
OR4	Ensure and maintain passenger safety and security during the initial move and operations.
OR5	A checklist/reporting mechanism is necessary for used with the operational readiness program.
OR6	Activation and operational readiness plan will be established early during the project.
OR7	Ensure all roles and responsibilities (operator, maintainer and user) documentation is signed off by relevant stakeholders.
OR8	Decisions should be taken by the activation team in a timely manner, and the decisions should be communicated across the planning organization.
OR9	Confirmation that all roles and responsibilities (operator, maintainer and user) are fully documented and communicated to all stakeholders.
OR10	A clear protocol for communication during the operational readiness program is required.
OR11	Maintain lines of communication with all the stakeholders during initial start-up and operations.
OR12	A formally dedicated activation and operational readiness team is required.
OR13	Ensure that regulatory and compliance requirements for all the processes and procedures are met.
OR14	Confirmation of an escalation process to higher management during operational readiness.
OR15	New facility objectives and performance outcomes should be documented and signed off by the operations team.
OR16	Progress update on the operations readiness plan will be managed and communicated to all stakeholders.
OR17	The project should have phased (soft) opening as part of its operational readiness plan.
OR18	Define and communicate the supporting department responsibilities during the initial phase of operations that includes the contractor and consultant as part of the stakeholders.
OR19	Prepare and communicate the grand opening activities.
OR20	Defines the documentation and contractual structure to support the use and execution of external services
OR21	Arrangement and agreement on the public communications, including service-scheduling impact.
OR22	Availability of new business and administration operational procedures and processes for all stakeholders.
OR23	Prepare and communicate all the new policies and procedures to stakeholders of the new facility.
OR24	A formal activation and operational readiness program.
Items	*People*
PR1	Government agencies such as police, immigration, and customs should be involved in the operational readiness program.
PR2	Training employee on the organization's new process and procedures
PR3	Ensure and maintain staff's safety and security during the initial move and operations.
PR4	Arrange and ensure staff training on new building systems.
PR5	New understanding and familiarization should be provided to the maintenance and operations team.
PR6	Availability of all the new staff's operating dependencies and move sequences.
PR7	New training material should be accessible to the maintenance and operation team.
PR8	Management willing to commit the necessary resources and make the operations implementation a high priority.
Items	*Technology*
TR1	Manage the safety and operational risks associated with the activation of the new systems.
TR2	All manuals and documentation to be made available during operational readiness and before actual operations.
TR3	Manage the impact on existing operations.
TR4	Availability of supporting department from suppliers and vendors during the initial phase of operations.
TR5	Ensure full testing and commissioning and integration of the critical systems of the new facility.
TR6	Ensure the validation and communication of the new phone numbers; new computer addresses to all relevant stakeholders and users.
TR7	Ensure system integration of the new facility to existing systems.
TR8	A plan for specialty disconnection/ reconnection requirements
TR9	Ensure adequate training and familiarization is provided for all the new maintenance and operational staff.
TR10	Operational trials and simulation for the new systems with critical stakeholders.
TR11	Ensure pre-occupancy stocking of all maintenance and operational supplies (spares) for the critical systems of all stakeholders.
TR12	Support and ensure the relocation of stakeholders' existing equipment as planned, with minimal operating disruptions.
TR13	Ensure and test for integration of the new facility to the existing systems.
TR14	Availability of all the new operating dependencies and move sequences.
TR15	Ensure adequate skills and competencies for all maintenance and operations staff of the new facility.
Measure	*Project success*
PS1	Meet time objectives
PS2	Meet cost/budget objectives
PS3	Deliver tangible benefits for the organization
PS4	Customers are satisfied with project outcomes
PS5	Project specifications met by handover
PS6	Stakeholder satisfaction with project management approach
PS7	Project team members' satisfaction with project management approach
PS8	Clearly identified benefits from the project
PS9	End user satisfaction with project outcomes
PS10	Use of effective project management processes
PS11	Overall satisfaction with project outcomes
PS12	Smooth project start-up
PS13	Overall stakeholder satisfaction
PS14	Return on investment

Table 2. *Input-output* models for feature importance analysis.

Model	Inputs	Output
1	FR, OR, PR, TR	*Project success* (PS)
2	FR, OR, PR, TR	*Operational resilience* (OpR)
3	PS1-PS14	*Project success* (PS)
4	TR1-TR15	*Technology resilience* (TR)
5	PR1-PR8	*People resilience* (PR)
6	OR1-OR24	*Organisation resilience* (OR)
7	FR1-FR7	*Facilities resilience* (FR)
8	PS1-PS14; TR1-TR15; PR1-PR8; OR1-OR24; FR1-FR7	*Operational resilience* (OpR)

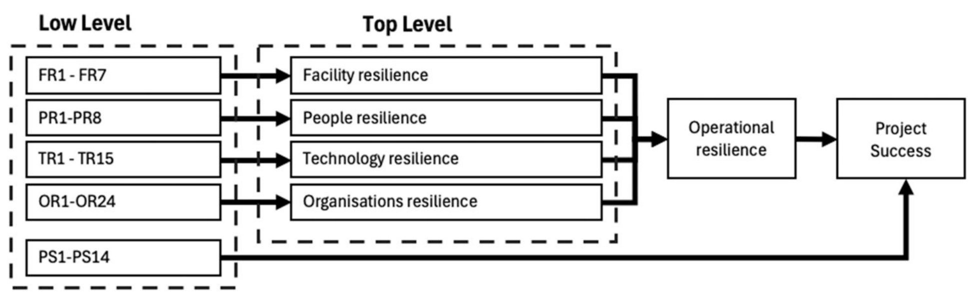


Figure 1. The research model depicting all factors contributing to OpR and PS.

low-level features alongside the four top-level factors to examine correlations with both OpR and PS.

Based on the research framework, eight *input–output* models (Table 2) were developed for feature and factor importance analysis. For each model, the relationships between the *inputs* and the *output* were quantified, enabling the determination of each *input's* relative influence. This procedure identifies the most and least impactful features for the given *output*. Repeating this analysis across all eight models provides a comprehensive understanding of the key determinants of both OpR and PS.

5. Analysis

5.1. Neural network

For this analysis, we employed a fully connected feed-forward neural network, given its strong capability to capture complex, nonlinear relationships between *input* features and continuous *output* variables, characteristics intrinsic to the problem under investigation. Unlike simpler models such as linear regression or decision trees, neural networks can uncover intricate patterns and interactions within the data, thereby enhancing predictive accuracy in regression tasks. Moreover, neural networks are highly compatible with advanced feature importance techniques such as LIME, SHAP, and PERM/PFI. This combination of a robust modelling approach and a comprehensive global-local analysis of feature relevance offers a powerful framework for uncovering the true underlying relationships in the dataset.

The *ReLU activation function* (Agarap 2018) was used, as the problem involves continuous *output* features, making it suitable for a regression task. The model was trained using the *Adam optimiser* (Kingma and Ba 2014) which adjusts the learning rate dynamically during training to improve performance. Training was conducted over a maximum of 200 *epochs*, with early stopping based on validation loss to prevent overfitting. In effect, our complete training dataset was passed through the learning algorithm to a maximum of 200 times. The assumption being that model accuracy would peak after training for this number of epochs (200) and then either stagnate or begin to decrease.

The learning rate, the number of hidden layers and neurons per hidden layer were all optimized using the SELECT method. The SELECT method is a method employed to optimize the training of ML models by consecutively assessing model performance against various sizes of training data, with the aim of finding the optimal balance between computational accuracy and cost. Essentially therefore, SELECT is a HPO technique that employs a sequential prediction model. It uses a subset of hyperparameter configurations from the search space to predict the learning curves for all configurations, in the process, reducing computational cost. The top-performing hyperparameter configurations are then selected based on these predictions. According to Smith and Wong (2024), the SELECT method has demonstrated superior performance compared to existing HPO benchmarks such as *Bayesian Optimisation with Gaussian process* (Snoek, Larochelle, and Adams 2012), *Tree Parzens estimator* (Rong et al. 2021), *Hyperband* (Li et al. 2018) and *Random search* (Bergstra and Bengio 2012).

5.2. The pipeline of analysis

Using the dataset collected from the Al-Mazrouie et al. (2021) survey, the pipeline of analysis is presented in Figure 2. The dataset for each *input-output* model is loaded into the pipeline and split into a training set, a validation set and a test set. The training set and validation set are used for HPO to select the top performing

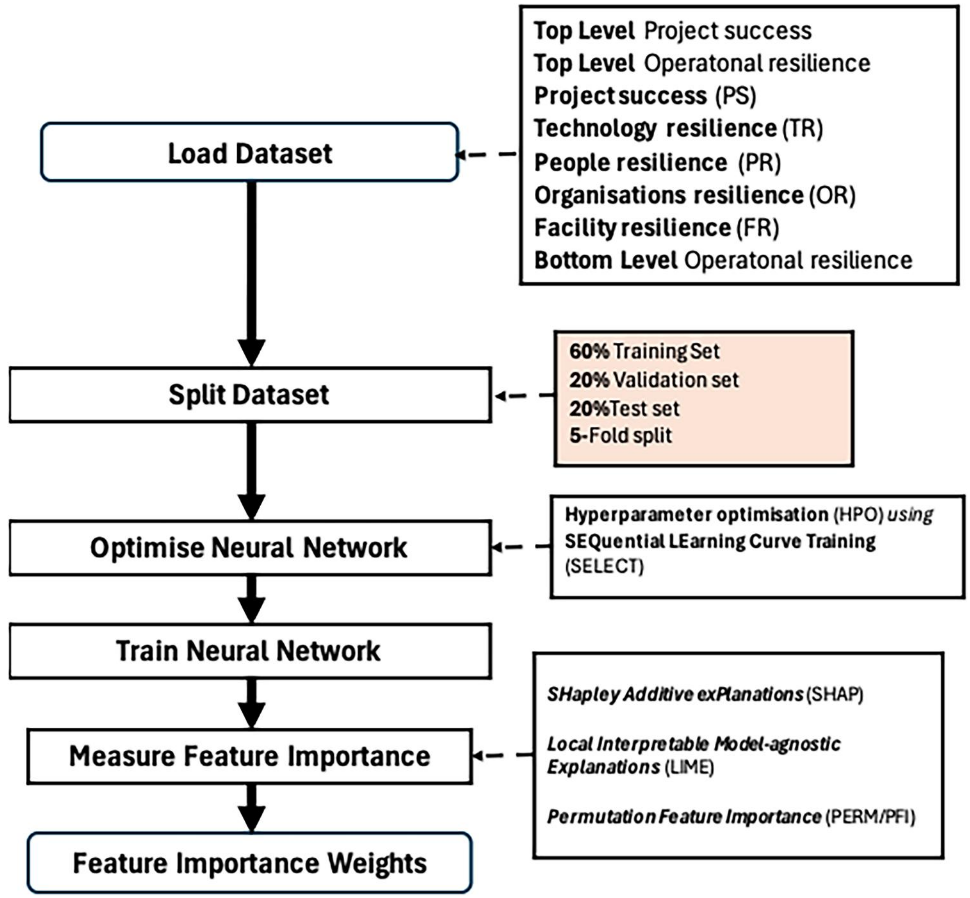


Figure 2. The pipeline for feature importance analysis.

hyperparameters for the neural network. Predictions are then made on the test set to determine the model predictive accuracy in MAE. The trained and optimized model is then combined with all three of SHAP, LIME and PERM/PFI for feature importance analysis.

To ensure robust and reliable results, the dataset of each *input-output* model was split into training, validation, and test sets with the ratio, 60%, 20% and 20% respectively (Wu et al. 2013). The data was also split 5 times for repeat analysis to mitigate the risk of overfitting and ensures that the final results are not dependent on any specific split of the data. This entire process is repeated for each of the eight *input-output* models to ensure a comprehensive analysis of feature relationships for both OpR and PS.

5.3. Software and tools

The analysis was implemented using *Python 3.11*, a versatile and widely used programming language for ML and data analysis due to its extensive libraries and ease of use (e.g. Bokrantz et al. 2024; Kasper, Land, and Thürer 2024; Olan et al. 2025; Uddin, Yan, and Lu 2025). The neural network was built and trained using *TensorFlow*, a powerful open-source ML framework that enables efficient training of deep learning models. For HPO, the SELECT method was applied, which is designed to efficiently predict the learning curves of hyperparameter configurations, reducing computational costs while maintaining model performance. Feature importance was analyzed using three tools: *eli5* for PERM/PFI, the shap library for SHAP and the lime library for LIME. The code for the analysis carrying out the feature importance for PERM/PFI, SHAP and LIME with the previously selected optimized neural network are shown in Figure 3.

The *outputs*, or results, were accumulation in *DataFrames* (i.e. tables), with the columns labelled, and then exported to allow for large numbers of analysis to be performed automatically. The code shown in Figure 4 allowed for this, combined with '*if*' logic, '*for*' loops and standardized document titles. However, while this part of the pipeline would be too large to show, the results were exported in the form of individual csv files for each feature importance tool.

The characteristics of the optimized neural networks; neurons per hidden layer, number of hidden layers and the learning rate were also recorded, with the resultant predictive performance of the optimized model in *Mean absolute error* (MAE) and *Root mean squared error* (RMSE). Covering all eight datasets, a folder in the form shown below in Figure 5 was created, the data in each file was then collected into a single excel file for processing and analysis.

6. Results

For each *input-output* model, the dataset is split into 80/20, i.e. 80% of the dataset is used to train the neural network

```
#Permutation Feature Importance
dataset_pd = dataset.drop(columns=predict)
test_features_pd = test_features.copy()
perm1 = PermutationImportance(model4,scoring = 'neg_mean_absolute_error',
                              random_state=1,n_iter=10).fit(test_features_pd,test_labels)
test_features_pd = pd.DataFrame(test_features,columns = dataset_pd.columns)
perm_result = eli5.explain_weights_df(perm1, feature_names = test_features_pd.columns.tolist())
perm_result= perm_result.drop(columns=['std'])
perm_result.columns=['feature_mae','mae_w']
perm_result = perm_result.sort_values(by="feature_mae").reset_index(drop=True)
perm_mae_weight_results["feature_mae"] = perm_result["feature_mae"]
perm_mae_weight_results = pd.concat([perm_mae_weight_results, perm_result["mae_w"]], axis =1)
perm_mae_weight_results.rename(columns={'mae_w': str(test_train_split_random_state)}, inplace=True)
#Shap Feature Importance
explainer = shap.KernelExplainer(model4.predict,test_features)
# Calculate the SHAP values for the test set
shap_values = explainer.shap_values(test_features)
feature_names = dataset.columns[:-1]
# Plot the SHAP summary plot
shap.summary_plot(shap_values, test_features, feature_names=dataset.columns[:-1])
shap_feature_importance = pd.DataFrame(list(zip(feature_names, np.abs(shap_values)[0].mean(0))),
                                       columns=['feature_name', 'feature_importance_vals'])
shap_feature_importance = shap_feature_importance.sort_values('feature_importance_vals',ascending = False)
shap_feature_importance.columns=['feature_mae','mae_w']
shap_feature_importance = shap_feature_importance.sort_values(by="feature_mae").reset_index(drop=True)
shap_mae_weight_results["feature_mae"] = shap_feature_importance["feature_mae"]
shap_mae_weight_results = pd.concat([shap_mae_weight_results, shap_feature_importance["mae_w"]], axis =1)
shap_mae_weight_results.rename(columns={'mae_w': str(test_train_split_random_state)}, inplace=True)
#LIME Feature Importance
# Create the Lime explainer
explainer = lime.lime_tabular.LimeTabularExplainer(training_data=train_features,
                                                   mode='regression',
                                                   feature_names=feature_names,
                                                   class_names=['output'],
                                                   verbose=True)
# Define the predict function for the neural network model
def predict_fn(x):
    return model4.predict(x)
# Generate Lime explanations for all instances in the test set
lime_feature_importance = []
lime_importance =[]
for i in range(len(test_features)):
    instance = test_features[i]
    explanation = explainer.explain_instance(instance,
                                             predict_fn,
                                             num_features=len(feature_names))
    lime_values = explanation.local_exp[0]
    lime_importance = pd.DataFrame(lime_values, columns=['feature_index', 'feature_importance_vals'])
    lime_importance['feature_name'] = lime_importance['feature_index'].apply(lambda idx: feature_names[idx])
    lime_importance = lime_importance.drop('feature_index', axis=1)
    lime_feature_importance.append(lime_importance)
# Combine Lime feature importance values for all instances
lime_feature_importance_all = pd.concat(lime_feature_importance).groupby('feature_name').mean().reset_index()
# Sort the Lime feature importance values
lime_feature_importance_all = lime_feature_importance_all.sort_values('feature_importance_vals', ascending=False)

lime_feature_importance_all
lime_feature_importance_all.columns=['feature_mae','mae_w']
lime_feature_importance_all = lime_feature_importance_all.sort_values(by="feature_mae").reset_index(drop=True)
lime_mae_weight_results["feature_mae"] = lime_feature_importance_all["feature_mae"]
lime_mae_weight_results = pd.concat([lime_mae_weight_results, lime_feature_importance_all["mae_w"]], axis =1)
lime_mae_weight_results.rename(columns={'mae_w': str(test_train_split_random_state)}, inplace=True)
clear_output(wait=False)
```

Figure 3. Analysis feature importance for PERM/PFI, SHAP and LIME analysis.

model and 20% of the dataset is used to test the trained model. The optimized model is selected as the trained model with the minimum MAE and RMSE. Three different well-known feature importance methods are used over the optimized model to measure the relative importance of each *input* towards each *output*. The whole process is repeated for 5 different splits of the same dataset. These feature importance methods are: (i) SHAP (ii) PERM/PFI (iii) LIME.

```
#Collect the average results
#Permutation
perm_mae_w_columns = perm_mae_weight_results.columns[perm_mae_weight_results.columns.get_loc('feature_mae') + 1:]
perm_mae_weight_results['Average_mae_w'] = perm_mae_weight_results[perm_mae_w_columns].mean(axis=1)
perm_average_w_noise_results["feature_mae"] = perm_result["feature_mae"]
perm_average_w_noise_results = pd.concat([perm_average_w_noise_results, perm_mae_weight_results['Average_mae_w']], axis =1
perm_average_w_noise_results.rename(columns={'Average_mae_w': 'Weight'}, inplace=True)
perm_mae_weight_results.sort_values(by = "Average_mae_w")
perm_mae_weight_results.to_csv("C:/Users/qsb20186/Desktop/Python ML/Collab_062024/Results/"+raw_data+"_PERM_weights.csv")
#SHAP
shap_mae_w_columns = shap_mae_weight_results.columns[shap_mae_weight_results.columns.get_loc('feature_mae') + 1:]
shap_mae_weight_results['Average_mae_w'] = shap_mae_weight_results[shap_mae_w_columns].mean(axis=1)
shap_average_w_noise_results["feature_mae"] = shap_feature_importance["feature_mae"]
shap_average_w_noise_results = pd.concat([shap_average_w_noise_results, shap_mae_weight_results['Average_mae_w']], axis =1
shap_average_w_noise_results.rename(columns={'Average_mae_w': 'Weight'}, inplace=True)
shap_mae_weight_results.sort_values(by = "Average_mae_w")
shap_mae_weight_results.to_csv("C:/Users/qsb20186/Desktop/Python ML/Collab_062024/Results/"+raw_data+"_SHAP_weights.csv")
#Lime
lime_mae_w_columns = lime_mae_weight_results.columns[lime_mae_weight_results.columns.get_loc('feature_mae') + 1:]
lime_mae_weight_results['Average_mae_w'] = lime_mae_weight_results[lime_mae_w_columns].mean(axis=1)
lime_average_w_noise_results["feature_mae"] = lime_feature_importance_all["feature_mae"]
lime_average_w_noise_results = pd.concat([lime_average_w_noise_results, lime_mae_weight_results['Average_mae_w']], axis =1
lime_average_w_noise_results.rename(columns={'Average_mae_w':  'Weight'}, inplace=True)
lime_mae_weight_results.sort_values(by = "Average_mae_w")
lime_mae_weight_results.to_csv("C:/Users/qsb20186/Desktop/Python ML/Collab_062024/Results/"+raw_data+"_LIME_weights.csv")

mae_results.to_csv("C:/Users/qsb20186/Desktop/Python ML/Collab_062024/Results/"+raw_data+"_MAE_Results.csv")
```

Figure 4. Code for the analysis allowing for *outputs* accumulated in DataFrames.

For each of the eight *input-output* models, the relative importance of each *input* is shown using each of the feature importance methods and the overall (the average relative importance over three methods). It is noted that the sum of relative importance of all *inputs* in the same model must be equal to 1. All relative importance values are between 0 and 1. An *input* with larger relative importance is deemed as more influential. However, the global impact of an *input* on the *output* could be either positive or negative.

6.1. Model 1, 2 and 3

Table 3 shows that in terms of Model 1 (*Input*= FR, OR, PR, TR; *Output*=PS), the relative importance of each component of resilience (i.e. FR, OR, PR, TR) on PS, by far the most important component is OR, followed by TR, FR and PR in that order.

Table 4 shows the results of the relative importance of the different resilience components on the hidden layers of OpR. Thus, in this Model 2 (*Input*= FR, OR, PR, TR; *Output*=OpR). Here, again, OR is the most important, but unlike its importance on project success, it does not dominate other components. TR has higher salience in this level.

Table 5 shows that in terms of Model 3 (*Input*= PS1-PS14; *Output*=PS), the relative importance of each of the 14 components on PS, by far the three most important component is PR6 (*Stakeholder satisfaction with project management approach*), followed by PS2 (*Meet cost/budget objectives*), and PS3 (*Deliver tangible benefits for the organisation*), in that order.

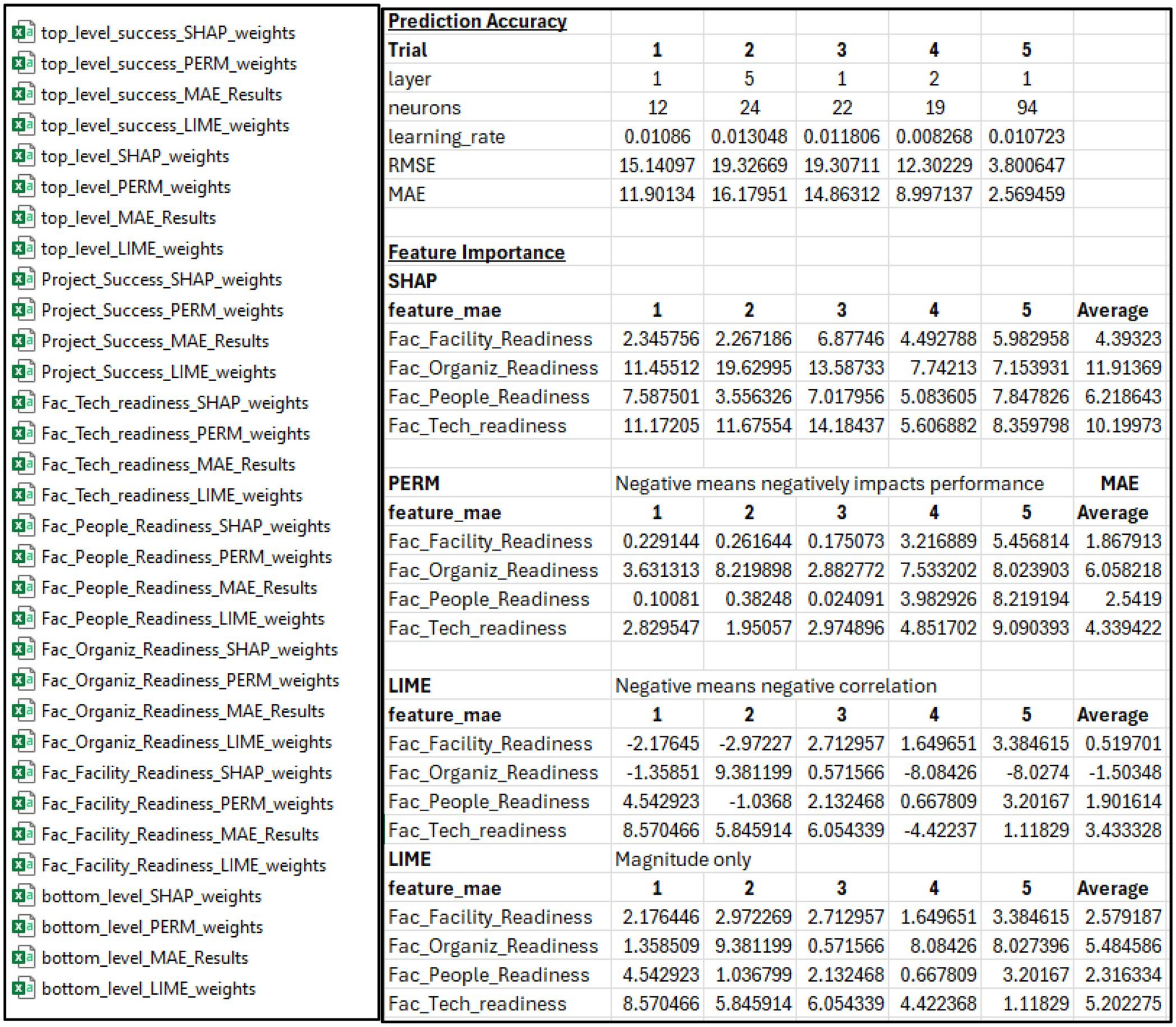
6.2. Model 4, 5, 6, and 7

Models 4 to 7 each show the relative importance of the individual items on each component of resilience, namely OpR, TR, PR, OR and FR.

Table 6 shows that in terms of Model 4 (*Input*= TR1-TR15; *Output*=TR), the relative importance of each of the 14 components of TR, by far the three most important component is TR14 (*Availability of all the new operating dependencies and move sequences*), followed by TR12 (*Support and ensure the relocation of stakeholders' existing equipment as planned, with minimal operating disruptions*), and TR11 (*Ensure pre-occupancy stocking of all maintenance and operational supplies (spares) for the critical systems of all stakeholders*), in that order.

Table 7 shows that in terms of Model 5 (*Input*= PR1-PR8; *Output*=PR), the relative importance of each of the 24 components of PR, by far the three most important component are PR6 (*Availability of all the new staff's operating dependencies and move sequences*), followed by PR2 (*Training employee on the organisation's new process and procedures*), and PR8 (*Management willing to commit the necessary resources and make the operations implementation a high priority*).

Table 8 shows that in terms of Model 6 (*Input*= OR1-OR24; *Output*=OR), the relative importance of each of the 14 components of OR, by far the three most important component is OR13 (*Ensure that regulatory and compliance requirements for all the processes and procedures are met*), followed by OR10 (*A clear protocol for communication during the operational readiness program is required*), and OR4 (*Ensure and



Prediction Accuracy						
Trial	1	2	3	4	5	
layer	1	5	1	2	1	
neurons	12	24	22	19	94	
learning_rate	0.01086	0.013048	0.011806	0.008268	0.010723	
RMSE	15.14097	19.32669	19.30711	12.30229	3.800647	
MAE	11.90134	16.17951	14.86312	8.997137	2.569459	
Feature Importance						
SHAP						
feature_mae	1	2	3	4	5	Average
Fac_Facility_Readiness	2.345756	2.267186	6.87746	4.492788	5.982958	4.39323
Fac_Organiz_Readiness	11.45512	19.62995	13.58733	7.74213	7.153931	11.91369
Fac_People_Readiness	7.587501	3.556326	7.017956	5.083605	7.847826	6.218643
Fac_Tech_readiness	11.17205	11.67554	14.18437	5.606882	8.359798	10.19973
PERM	Negative means negatively impacts performance					MAE
feature_mae	1	2	3	4	5	Average
Fac_Facility_Readiness	0.229144	0.261644	0.175073	3.216889	5.456814	1.867913
Fac_Organiz_Readiness	3.631313	8.219898	2.882772	7.533202	8.023903	6.058218
Fac_People_Readiness	0.10081	0.38248	0.024091	3.982926	8.219194	2.5419
Fac_Tech_readiness	2.829547	1.95057	2.974896	4.851702	9.090393	4.339422
LIME	Negative means negative correlation					
feature_mae	1	2	3	4	5	Average
Fac_Facility_Readiness	-2.17645	-2.97227	2.712957	1.649651	3.384615	0.519701
Fac_Organiz_Readiness	-1.35851	9.381199	0.571566	-8.08426	-8.0274	-1.50348
Fac_People_Readiness	4.542923	-1.0368	2.132468	0.667809	3.20167	1.901614
Fac_Tech_readiness	8.570466	5.845914	6.054339	-4.42237	1.11829	3.433328
LIME	Magnitude only					
feature_mae	1	2	3	4	5	Average
Fac_Facility_Readiness	2.176446	2.972269	2.712957	1.649651	3.384615	2.579187
Fac_Organiz_Readiness	1.358509	9.381199	0.571566	8.08426	8.027396	5.484586
Fac_People_Readiness	4.542923	1.036799	2.132468	0.667809	3.20167	2.316334
Fac_Tech_readiness	8.570466	5.845914	6.054339	4.422368	1.11829	5.202275

Figure 5. Created folder.

Table 3. Three relative importance results of Model 1 (*Project success*).

Inputs	SHAP	PERM/PFI	LIME	Overall
FR	0.142384	0.119742	0.14056	0.134228667
OR	0.622187	0.716836	0.608864	0.649295667
PR	0.079926	0.084528	0.070369	0.078274333
TR	0.155503	0.078894	0.180207	0.138201333

Table 4. Three relative importance results of Model 2 (*Operational resilience*).

Inputs	SHAP	PERM/PFI	LIME	Overall
FR	0.139605	0.085664	0.169634	0.131634333
OR	0.35762	0.483203	0.334943	0.391922
PR	0.197285	0.1049	0.152246	0.151477
TR	0.305491	0.326233	0.343177	0.324967

maintain passenger safety and security during the initial move and operations), in that order.

Table 9 shows that in terms of Model 7 (*Input*= FR1-FR7; *Output*=FR), the relative importance of each of the 7 components of FR, by far the three most important component are FR5 (*Ensure that all the new fit outs and furniture installation and acceptance are completed*), followed by FR2 (*Ensure pre-occupancy stocking of all maintenance and operational supplies for all stakeholders*), and FR1 (*Operational trials and simulation with critical stakeholders*), in that order. In Appendix A, we show the three relative importance results of Model 8 (i.e. detailed resilience components for '*Operational resilience*'). For brevity, this table is not reported on in our results.

7. Discussions

Among the four resilience factors examined (i.e. '*Facilities resilience*', '*People resilience*', '*Technology resilience*', and '*Organisation resilience*'), '*Organisation resilience*' exhibited the greatest relative impact on '*Project success*'. This aligns with

Table 5. Three relative importance results of Model 3 (components of *Project success*).

Inputs	SHAP	PERM/PFI	LIME	Overall
PS1	0.073108495	0.131684105	0.031147425	0.078646675
PS10	0.065737602	0.040482159	0.068034492	0.058084751
PS11	0.071153821	0.043197244	0.08420093	0.066183998
PS12	0.074501785	0.025394681	0.124561847	0.074819438
PS13	0.077771802	0.025071646	0.097013375	0.066618941
PS14	0.073878425	0.033670486	0.059613686	0.055720866
PS2	0.075839881	0.152846505	0.025644964	0.084777117
PS3	0.071294598	0.130723617	0.042679461	0.081565892
PS4	0.056916193	0.044557178	0.063948528	0.055140633
PS5	0.085986295	0.038035719	0.120410621	0.081477545
PS6	0.079474729	0.084514592	0.123756165	0.095915162
PS7	0.070738692	0.078062778	0.035751281	0.061517584
PS8	0.058811693	0.058798432	0.069832394	0.06248084
PS9	0.06478599	0.112960857	0.053404831	0.077050559

Table 6. Three relative importance results of Model 4 (*Technology resilience*).

Inputs	SHAP	PERM/PFI	LIME	Overall
TR1	0.075504633	0.065623485	0.042965438	0.061364519
TR2	0.064358969	0.070958224	0.074988892	0.070102028
TR3	0.081938424	0.062164559	0.074782358	0.07296178
TR4	0.062589038	0.040712261	0.07350833	0.058936543
TR5	0.076531239	0.078686136	0.082841033	0.079352803
TR6	0.062870279	0.072011807	0.057775624	0.064219237
TR7	0.072786278	0.033593841	0.039892141	0.04875742
TR8	0.059493665	0.042458072	0.088280749	0.063410829
TR9	0.065247794	0.068556063	0.014993447	0.049599101
TR10	0.069452398	0.080092405	0.037251074	0.062265292
TR11	0.051859521	0.099819141	0.093699724	0.081792795
TR12	0.069521289	0.084079067	0.10458487	0.086061742
TR13	0.063773377	0.059176814	0.027529851	0.050160014
TR14	0.062860002	0.066985762	0.130804448	0.086883404
TR15	0.061213093	0.075082363	0.05610202	0.064132492

Table 7. Three relative importance results of Model 5 (*People resilience*).

Inputs	SHAP	PERM/PFI	LIME	Overall
PR1	0.123144666	0.125875052	0.104887195	0.117968971
PR2	0.124375141	0.187491976	0.139970138	0.150612418
PR3	0.127170594	0.049925537	0.109679536	0.095591889
PR4	0.135028314	0.069628672	0.106325427	0.103660804
PR5	0.128417608	0.101339279	0.084996494	0.104917794
PR6	0.13184117	0.146003568	0.244956279	0.174267006
PR7	0.110948377	0.108203262	0.133691069	0.117614236
PR8	0.119074129	0.211532654	0.07549386	0.135366881

Table 8. Three relative importance results of Model 6 (*Organisation resilience*).

Inputs	SHAP	PERM/PFI	LIME	Overall
OR1	0.046279381	0.037247677	0.014690162	0.032739073
OR2	0.04928944	0.020617739	0.065944944	0.045284041
OR3	0.042534128	0.036001896	0.028647498	0.035727841
OR4	0.041825726	0.043103159	0.059634026	0.048187637
OR5	0.051979965	0.027392219	0.042343509	0.040571898
OR6	0.035103394	0.051308788	0.019578721	0.035330301
OR7	0.043804484	0.057024806	0.03981316	0.046880817
OR8	0.033109103	0.048457504	0.040584599	0.040717069
OR9	0.039590116	0.044842126	0.054218081	0.046216774
OR10	0.045376503	0.062800081	0.043634392	0.050603659
OR11	0.051080975	0.042225469	0.040024471	0.044443638
OR12	0.046217469	0.034247467	0.039266885	0.039910607
OR13	0.047513261	0.046322194	0.065015602	0.052950352
OR14	0.038253855	0.033703222	0.051989113	0.041315397
OR15	0.037395692	0.043985138	0.044608704	0.041996511
OR16	0.045848182	0.024882964	0.056976997	0.042569381
OR17	0.040510085	0.044290526	0.038734683	0.041178431
OR18	0.047216431	0.037377608	0.052019455	0.045537831
OR19	0.035013516	0.035904204	0.043962711	0.038293477
OR20	0.039418808	0.047824378	0.002855418	0.030032868
OR21	0.038889836	0.034789001	0.021539939	0.031739592
OR22	0.034573364	0.046544844	0.051380411	0.044166206
OR23	0.037861628	0.058426567	0.039280545	0.04518958
OR24	0.031314658	0.040680422	0.043255973	0.038417018

Table 9. Three relative importance results of Model 7 (*Facilities resilience*).

Inputs	SHAP	PERM/PFI	LIME	Overall
FR1	0.161221137	0.134386575	0.14369866	0.146435457
FR2	0.131342421	0.138171817	0.203426016	0.157646751
FR3	0.146693657	0.149063186	0.074920135	0.123558993
FR4	0.146687227	0.150371063	0.079477201	0.12551183
FR5	0.130531434	0.170240137	0.32741462	0.209395397
FR6	0.14434156	0.117674604	0.032649428	0.098221864
FR7	0.139182564	0.140092619	0.13841394	0.139229708

literature emphasizing the historical focus on organizational-level resilience (Scholten, Stevenson, and van Donk 2019). '*Organisation resilience*' is recognised as a vital organizational competence (de Oliveira Teixeira and Werther 2013; Koh et al. 2024; Pratono 2022; Wang et al. 2022), enabling organizations to withstand disruptive threats and maintain operational viability (Burnard, Bhamra, and Tsinopoulos 2018; Burnard and Bhamra, 2011). Research highlights the importance of organizational structure (Williams et al. 2017) and firm resources (Richtnér and Löfsten 2014) in fostering resilience. Given the potential consequences of disruptions, proactive action is essential to sustain functionality and competitiveness, making '*Organisation resilience*' the most effective pathway for overcoming disruptions. AI/ML provides additional support by enabling intelligent responses to both internal and external disruptions.

While '*Organisation resilience*' had the strongest influence on '*Operational resilience*', its dominance was reduced relative to '*Project success*' due to the higher salience of '*Technology resilience*'. This underscores that '*Organisation resilience*', defined as an organization's capacity to recover, restore, and adapt under disruptions, is foundational for '*Operational resilience*', or the continued delivery of critical services amid discontinuities (Galaitsi et al. 2023; Hepfer and Lawrence 2022). These findings support the view of '*Organisation resilience*' and '*Operational resilience*' as a business continuity dyad (Galaitsi et al. 2023), contrasting with studies that consider '*Organisation resilience*' to inherently encompass '*Operational resilience*' (Essuman, Boso, and Annan 2020; Holgado et al. 2024).

Within '*Project success*' components, PR6 (stakeholder satisfaction with the project management approach) was most influential, reflecting the importance of stakeholder perceptions in resilience outcomes (Chmutina and Rose 2018; Fontainha et al. 2022; Yang et al. 2022). Infrastructure projects involve heterogeneous stakeholders, and collaboration is crucial to ensuring satisfaction with resilience measures (Chipulu et al. 2019; Morkan et al. 2023; Yang et al. 2022).

For '*Technology resilience*', TR14 (availability of all new operating dependencies and move sequences) emerged as the most critical component. System interconnectivity in complex infrastructures can exacerbate vulnerabilities, making the management of operating dependencies essential for designing failsafe mechanisms and developing resilient systems (Ouyang 2014; Zio 2016).

Table 10. Summary of findings.

Our findings	Type	Evidence presented
'*Organisational resilience*' is the most important top-level factor	Reinforced	Confirmed by Model 1: OR had a relative importance score of ∼0.65 (SHAP, LIME, PERM/PFI average) for predicting Project Success.
Ranked order of factor importance: *OR* > *TR* > *FR* > *PR*	New	ML-derived ranking shown in Model 1 results table—this exact ranking was not derived in the previous SEM-based study.
Different dominance patterns for OpR vs PS	New	In Model 2 (OpR), OR still led but was less dominant, TR showed greater influence compared to PS.
Individual 2nd order features identified as most important within each category	New	Model 3–7 results list sub-factors like PR6, OR13, TR14, FR5 etc. as having highest average feature importance.
Use of SHAP, LIME, and PERM/PFI provides interpretability triangulation	Reinforced	All three methods applied and averaged; methodological justification provided.
ML confirms and enhances the previously developed typology	Reinforced	Four-dimensions of resilience structure retained (*FR*, *PR*, *OR*, *TR*), reaffirming the statistical model from Al-Mazrouie et al. (2021).

Among '*People resilience*' components, PR6 (availability of operating dependencies for new staff) and PR2 (training on new processes) were most significant. Effective onboarding and targeted training are crucial to maintain adaptability, psychological safety, and operational continuity (Borg et al. 2022; Dusenberry and Robinson 2020).

Key '*Organisation resilience*' components included regulatory and compliance adherence, clear communication protocols, and user safety and security, consistent with literature emphasizing compliance as a proactive resilience mechanism (Herrmann 2007; Itani et al. 2024; Øyri and Wiig 2022). For '*Facilities resilience*', FR5 (completion of new fit-outs and furniture acceptance) was the most important, though this contrasts with prior studies that emphasize the temporal embedding of resilience across the project lifecycle (Piperca and Floricel 2023).

Post-hoc analysis of Al-Mazrouie et al. (2021) data reinforced existing knowledge that '*Organisation resilience*' is a top-level resilience factor (Börekçi et al. 2021; Koh et al. 2024) while revealing novel insights. Specifically, the ranking of top-level factors differed: *OR* > *TR* > *FR* > *PR*, in contrast to the original *TR* > *OR* > *PR* > *FR* ordering. Differences in dominance patterns between '*Operational resilience*' and '*Project success*' were also observed: '*Organisation resilience*' led in both contexts but was less dominant in '*Operational resilience*', with '*Technology resilience*' exerting a stronger effect. Second-order feature analysis highlighted sub-factors PR6, OR13, TR14, and FR5 as having the highest average feature importance.

Finally, the study demonstrates the value of SHAP, LIME, and PERM/PFI for interpretability triangulation and confirms ML's utility in validating and enhancing pre-existing typologies. The four-part resilience structure (FR, PR, OR, TR) proposed by Al-Mazrouie et al. (2021) was retained, supporting its continued relevance. Table 10 summarizes these findings.

8. Conclusions

Critical infrastructure project assets are often vulnerable to breakdowns, discontinuities, and operational disruptions, which can trigger cascading effects across globally networked systems and contribute to project failure. These disruptions, however, can be effectively managed by cultivating resilience as a core organizational capability. Resilience enables infrastructure assets to maintain functionality and performance amid disruptions, preserving long-term viability.

With increasing computational capacity, operations and project management practices are increasingly supported by systems capable of processing and analysing large datasets. Frameworks such as ORAT are evolving towards integration with Industry 4.0 technologies, particularly ML. Embedding ML tools within infrastructure planning and operations supports data-driven analysis and informed decision-making, strengthening the capacity of systems to withstand disruptions and achieve successful outcomes.

Focusing on the readiness dimension, which emphasizes early threat detection and prevention, this research develops an empirically validated resilience model that identifies correlations between key resilience factors and project success. Neural network-based ML techniques were employed to construct a robust model for their examination. Findings indicate that '*Organisational resilience*' is the most influential dimension, significantly impacting '*Project success*' in the context of safeguarding the operational integrity of critical infrastructure through threat mitigation against their stability.

While existing literature underscores the benefits of resilience for critical infrastructure and highlights the use of resilience/readiness models for system performance prediction, ML can further enhance these models with sophisticated analytical capabilities. A prevailing challenge is that ML-enabled resilience models often lack empirical validation, raising concerns about their accuracy, reliability, and real-world applicability. This study addresses this gap by applying neural network-based ML techniques which involved incorporating three feature importance techniques: SHAP, LIME, and PERM/PFI, to explore correlations between resilience and project success, advancing understanding of how ML can strengthen critical infrastructure resilience.

Enhancing resilience remains a core objective for project managers, resilience professionals, and ORAT practitioners. The increasing complexity, interdependency, and uncertainty of infrastructure systems make developing effective resilience models challenging. Advanced ML technologies are crucial in addressing these challenges, providing dynamic, real-time, and self-adaptive decision support capable of efficiently harnessing large volumes of infrastructure data. This study contributes to both theoretical discourse and managerial practice, offering an empirically validated, ML-enabled approach that identifies correlations between key resilience factors and project success, and therefore, is capable of improving infrastructure resilience proactively and reliably.

8.1. Contributions to theory

The study makes several theoretical contributions to the discourse on ML-enabled resilience by addressing a critical gap in existing resilience and project management models, thereby advancing the field, which has traditionally relied on conventional risk management assessments for safeguarding operational integrity and mitigating threats. It extends prior research on resilience and readiness in critical infrastructure by examining contextual factors that heighten asset vulnerability, thereby building on and advancing the work of Al-Mazrouie et al. (2021). The proposed model systematically establishes the relationship between key resilience factors and project success, offering a quantifiable framework with high predictive accuracy and robust interpretability for understanding how resilience influences project outcomes. Moreover, the model generates novel insights into the role of ML in supporting resilience-oriented decision-making, particularly within critical infrastructure, by analysing complex datasets and facilitating optimal decisions across diverse scenarios in anticipation of potential disruptions. The study further provides empirically validated evidence of the effective application of neural network-based ML models, demonstrating their capacity to refine and enhance existing critical infrastructure resilience frameworks, especially those emphasizing readiness, by improving accuracy, integrity, and reliability.

Through the integration of rigorous training and performance optimization with three ML feature importance techniques (SHAP, LIME, and PERM/PFI), complementary and triangulated insights are developed. This approach to analysing the data offers several distinct benefits, highlighting the study's contribution through the capability of the internal algorithms to extract insights that go beyond conventional statistics, standard empirical or heuristic techniques. A fully optimized ANN is particularly advantageous for detecting and leveraging non-linear and complex relationships between features to determine their association with the predicted variable. Optimizing the ANN for the dataset ensures that even the most challenging patterns are captured within the trained model. Combining this ML model with three different feature importance algorithms, each employing its own approach to determine feature relationships, compounds the search for relationships and validates the significance of this integrated analytical framework. Specifically, LIME detects local relationships in the data, PFI quantifies not only the impact of each feature on model performance but also identifies those of limited relevance, and SHAP measures each feature's contribution to the predicted performance metric, including interdependent relationships. Comparing all three approaches provides insights into features that are consistently influential across methods as well as those that are case or tool dependent, adding valuable context to the detection of relationships. Integrating a powerful, dataset optimized ANN with three complementary feature importance tools thus produces knowledge that exceeds the capability of any individual components of the combined method.

A key advantage of these techniques lies in their ability to provide both global and local interpretability, ensuring that model outputs remain consistent with domain knowledge. In contrast, the complexity of alternative architectures such as ANNs, RNNs, and LSTMs renders it extremely challenging to discern how individual input features contribute to predictions. Furthermore, feature importance techniques enable feature selection and dimensionality reduction, thereby enhancing efficiency without compromising reliability.

Overall, the findings demonstrate how advanced technologies such as ML can be harnessed to address resilience challenges in critical infrastructure, emphasizing the importance of proactive strategies focused on early threat detection and mitigation.

By identifying 'Organisation resilience' as the primary factor influencing project success across critical infrastructure platforms, the study reinforces the established role of organizational factors as a central dimension of resilience (Börekçi et al. 2021; Burnard, Bhamra, and Tsinopoulos 2018; Burnard and Bhamra 2011; Koh et al. 2024) while also generating new knowledge. Specifically, the findings provide a ranked ordering of factor importance in critical infrastructure resilience and reveal differentiated patterns of dominance for operational resilience in relation to project success.

8.2. Contributions to practice

The study generates significant practical impact across multiple domains. The incorporation of ML and feature importance tooling provides an objective tool for analysis, which delivers complex insights with clear metrics and rankings for what is important, based purely on how an optimized ML model can interpret relationships. This framework not only supports evidence-based decision making but also enhances efficiency by reducing the need for manual assessments and allows the model to be updated with new data, supporting ongoing monitoring and continuous improvement of resilience strategies.

The study also provides tangible benefits for project managers, resilience specialists, and ORAT practitioners engaged with critical infrastructure by delivering actionable insights into the resilience factors that most strongly influence project success. Access to this information supports more informed and evidence-based decision-making in areas such as resource allocation, risk mitigation, and proactive interventions, ensuring timely threat detection and the prevention of operational disruptions. Being empirically validated, the model enhances real-world applicability, thereby addressing a gap previously observed in the literature. Additionally, the model promotes evidence-based decision-making, strengthening overall operational resilience.

By integrating ML into the resilience assessment of critical infrastructure, the study further advances practical impact through increased transparency, fostering trust and confidence among critical infrastructure stakeholders. This transparency allows those who are not technical, to comprehend model parameters, particularly the input–output structures used to assess feature and factor importance. Moreover, it underscores the value of feature importance techniques for identifying the key drivers of resilience (Binder et al. 2016; Mathews 2019; Sadeghi et al. 2024).

It is important to note, however, that the resilience dimensions employed in this study, while theoretically grounded and empirically validated post-hoc based on Al-Mazrouie et al. (2021), are not universally fixed. Critical infrastructure may necessitate context-specific (e.g. industry-based) sub-factor configurations. Effective implementation requires managers to consider the unique characteristics of their assets and adapt the model accordingly. As resilience lacks universal solutions, tailoring the model to platform- or industry-specific contexts is essential (Fontainha et al. 2022). The study further emphasizes that organizational resilience plays a pivotal role in enabling critical infrastructures to prepare for, respond to, adapt, and recover from disruptions, thereby sustaining operational continuity.

8.3. Study limitations and future research opportunities

Despite its contributions, this study has several limitations. First, it focuses exclusively on the readiness dimension of resilience. While widely acknowledged as a critical precursor to successful project implementation, this narrow focus limits the development of a comprehensive neural network-based ML model for infrastructure resilience. Future research should explore other dimensions to generate more extensive insights. Given that resilience is dynamic, with different metrics applicable at each dimension (Wang et al. 2024), separate neural network-based ML models may be necessary to comprehensively assess resilience across different dimensions.

Second, the study also relies on a *post-hoc* analysis of secondary data originally reported by Al-Mazrouie et al. (2021). Although the dataset aligns with the study's objectives, it may also be somewhat dated. Updating the dataset through new surveys or combining it with other sources could provide more current, contextually relevant insights. Concerns may arise regarding whether the identified factor relationships were sufficiently validated. However, the model builds on a pre-validated framework developed and reported by Al-Mazrouie et al. (2021), via a rigorous six-stage methodology, including a Delphi study and a large-scale survey of operations and project management professionals. The study extends this validated framework using neural network-based ML techniques to uncover deeper patterns, assess predictive accuracy, and evaluate feature importance. Future research adapting the model to different infrastructure types, geographic contexts, or evolving risk environments would benefit from additional expert validation.

Third, the dataset focuses on a single infrastructure type (i.e. airports), which may limit generalizability. The dataset may not capture the full diversity of resilience factors required for robust model training. Future studies could expand the dataset or apply the model to other infrastructure domains (e.g. dry ports, power plants, hospitals) and sectors (e.g. supply chains, Industry 4.0), advancing interdisciplinary scholarship (AlMalki and Durugbo 2024; Hajoary, Balachandra, and Garza-Reyes 2024; Stentoft et al. 2021).

Fourth, although the integration of the three ML feature importance techniques (SHAP, LIME, and PERM/PFI), can provide complementary and triangulated insights, their use is not without limitations when compared with alternative architectures such as ANNs, RNNs, and LSTMs. One major constraint is their high demand for resources, including extensive data, coupled with intensive computational requirements and longer runtimes. Additionally, these techniques are prone to approximation errors, which often arise from oversimplifying complex decision boundaries (Knab et al. 2025). However, such disadvantages can be mitigated through computational refinements or by adopting enhanced variants of these techniques, such as TreeSHAP, or alternative approaches. Examples include *Counterfactual Explanations*, which identify minimal *input* changes needed to alter predictions (Del Ser et al. 2024; Verma, Dickerson, and Hines 2021), and *Feature Permutation Importance with Conditional Sampling*, which preserves feature correlations during permutation (Debeer and Strobl, 2020; Lobo, Neuvial, and Thirion 2025).

Finally, behavioural dimensions of ML and neural networks in infrastructure resilience remain underexplored. While technical aspects dominate current research, understanding how human behaviour, cognitive biases, and motivational factors influence resilience-related decision-making could enhance the delivery and long-term sustainability of critical infrastructure systems (Bokrantz et al. 2024; Scholten et al. 2023).

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No potential conflict of interest was reported by the authors.

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Appendix A. Three relative importance results of Model 8 (detailed resilience components for operational resilience)

Inputs	SHAP	PERM/PFI	LIME	Overall
FR1	0.018364621	0.005668809	0.016905557	0.013646329
FR2	0.014959022	0.00875308	0.022557995	0.015423366
FR3	0.019260327	0.010505887	0.010321902	0.013362705
FR4	0.017509352	0.009681075	0.00982217	0.012337532
FR5	0.015775273	0.012891452	0.036517606	0.02172811
FR6	0.017459967	0.0112132	0.004879963	0.011184377
FR7	0.017059044	0.013799253	0.017218631	0.016025643
OR1	0.015683663	0.010977722	0.003831538	0.010164308
OR10	0.027045488	0.025234549	0.024896395	0.025725477
OR11	0.021536831	0.024185628	0.013288898	0.019670452
OR12	0.012062738	0.01630281	0.009463995	0.012609848
OR13	0.021554007	0.021646973	0.042480613	0.028560531
OR14	0.014865631	0.019612874	0.026676614	0.02038504
OR15	0.01846901	0.025186608	0.024603437	0.022753018
OR16	0.015958232	0.02143342	0.026784429	0.021392027
OR17	0.018763383	0.024975559	0.023509303	0.022416082
OR18	0.018511679	0.030680316	0.017824311	0.022338769
OR19	0.013999761	0.01592023	0.019069553	0.016329848
OR2	0.015444296	0.016839331	0.028336499	0.020206709
OR20	0.016602691	0.017693408	0.0064809	0.013592333
OR21	0.017375032	0.019666271	0.019223266	0.018754856
OR22	0.012760629	0.01786482	0.024301542	0.018308997
OR23	0.017982365	0.013944529	0.019204196	0.017043697
OR24	0.018842529	0.021999986	0.031916568	0.024253028
OR3	0.016491332	0.019942513	0.010637727	0.015690524
OR4	0.019256648	0.01452168	0.027488923	0.020422417
OR5	0.02076253	0.024962462	0.009809534	0.018511509
OR6	0.017339601	0.018573416	0.016002101	0.017305039
OR7	0.015870451	0.023782993	0.020712468	0.020121971
OR8	0.018125072	0.014997324	0.024062012	0.019061469
OR9	0.018347431	0.023682569	0.019029198	0.020353066
PR1	0.020246946	0.009801153	0.011885618	0.013977906
PR2	0.019214351	0.011198674	0.012302275	0.014238433
PR3	0.01948964	0.011090008	0.011462649	0.014014099
PR4	0.015904673	0.010348398	0.010125367	0.012126146
PR5	0.022327603	0.01796973	0.012065983	0.017454439
PR6	0.01887675	0.01100814	0.028765439	0.01955011
PR7	0.016295856	0.02461643	0.015340339	0.018750875
PR8	0.016898076	0.02160337	0.007116507	0.015205984
PS1	0.00097189	0.001181088	0.000597701	0.000916893
PS10	0.001888796	0.009414607	0.002137256	0.00448022
PS11	0.000728031	0.005706802	0.000368218	0.002267684
PS12	0.002367358	0.008210748	0.002740513	0.00443954
PS13	0.002575068	0.005192942	0.003861939	0.00387665
PS14	0.001603781	0.00387468	0.000743179	0.00207388
PS2	0.000702353	0.001529438	0.000562969	0.000931587
PS3	0.002031869	0.001436753	0.000862499	0.001443707
PS4	0.001380737	0.005625267	0.003697057	0.003567687
PS5	0.002774512	0.010888198	0.00533337	0.006332027
PS6	0.005797319	0.0057645	0.005142388	0.005568069
PS7	0.001767351	0.007022938	0.001212609	0.003334299
PS8	0.001703147	0.007681551	0.002374963	0.003919887
PS9	0.001587532	0.005382907	0.002402717	0.003124385
TR1	0.02542555	0.014524804	0.016449151	0.018799835
TR10	0.017917037	0.015245629	0.010327887	0.014496851
TR11	0.016942602	0.012427966	0.027143849	0.018838139
TR12	0.015324706	0.01299879	0.018699056	0.015674184
TR13	0.018898194	0.014634688	0.00759638	0.013709754
TR14	0.018450824	0.020750791	0.038957288	0.026052968
TR15	0.015527651	0.011108355	0.014365491	0.013667166
TR2	0.015644187	0.010070459	0.017400481	0.014371709
TR3	0.026151842	0.022532254	0.021992409	0.023558835
TR4	0.019331134	0.025414908	0.016654376	0.020466806
TR5	0.014556066	0.014759943	0.012949685	0.014088565
TR6	0.016452808	0.015274889	0.011159483	0.014295727
TR7	0.022775277	0.022050505	0.008475421	0.017767068
TR8	0.020126237	0.017521527	0.024245299	0.020631021
TR9	0.015303608	0.016995419	0.004624344	0.01230779