Review of Applied Science and Technology

Volume: 6; **Issue:** 1
Pages: 263– 279

open access

Crossref

Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays

Mohammad Shoriful Hossan Shohel[1];

[1]. BSc IN EEE, Ahsanullah University of Science and Technology, Bangladesh
Professional Electrical & Instrument Control Engineer in Petrochemical Industry Group;
Email: shoriful.cv@gmail.com

Doi: 10.63125/cm1c2c20
Received: 15 September 2021; **Revised:** 24 October 2021; **Accepted:** 19 November 2021; **Published:** 13 December 2021;

Abstract

Every skipped inspection leaves a mark that does not show up until later. When the pandemic forced manufacturers to thin their crews, restrict who could enter a plant, and postpone anything that was not an emergency, the work that got deferred first was often the electrical maintenance that keeps workers safe and equipment running: arc-flash studies left unrenewed, breakers and relays untested, thermographic scans skipped, preventive maintenance on aging switchgear pushed to a later date that kept receding. The result, in brownfield facilities already running on old infrastructure, was an accumulating backlog, a debt of deferred maintenance that quietly raised both the danger to workers and the likelihood of electrical failure. This study treats that debt as the central problem and asks how facilities pay it down: how they surface the backlog, size the risk hidden inside it, and work it off in the order that most reduces harm. It models a combined worker-safety and reliability recovery outcome as a function of six capabilities: maintenance-backlog assessment, deferred-risk quantification, worker-exposure control, electrical-reliability restoration, recovery scheduling and resourcing, and an integrating construct of post-pandemic maintenance recovery maturity. Evidence came from a structured five-point Likert survey completed by 154 valid respondents out of 172 distributed, an 89.5% valid response rate, drawn from maintenance and reliability engineers, electrical and power engineers, EHS and safety managers, plant and facilities managers, and maintenance planners, of whom 70.1% had directly managed electrical maintenance or safety through the pandemic and its aftermath. The data were analyzed with descriptive statistics, Cronbach's alpha, Pearson correlation, multiple regression, a maturity index, and a capability priority matrix. Every capability was rated in the high band, led by the combined safety-reliability recovery outcome at a mean of 4.29 and worker-exposure control at 4.20; reliability was strong, with alpha from 0.83 to 0.94. All correlations were positive and significant, the strongest being $r = 0.80$ between post-pandemic maintenance recovery maturity and the recovery outcome. The regression model explained 74.9% of the variance in the outcome, $R^2 = 0.749$, adjusted $R^2 = 0.739$, $F(6,147) = 73.15$, $p < 0.001$, with post-pandemic maintenance recovery maturity the leading predictor, $\beta = 0.32$, ahead of worker-exposure control, $\beta = 0.25$, and electrical-reliability restoration, $\beta = 0.20$. The central finding is that safety and reliability recover together, and stay recovered, only when a facility treats its pandemic maintenance backlog as a measured risk debt to be worked down deliberately, recovering the record, assessing the danger, prioritizing by risk, and restoring and retesting, rather than catching up haphazardly as time and budget allow.

Keywords

Maintenance backlog; Worker exposure; Electrical reliability; Brownfield facilities; Post-pandemic recovery.

INTRODUCTION

Every skipped inspection leaves a mark that does not show up until later. When the pandemic forced manufacturers to thin their crews, restrict who could enter a plant, and postpone anything that was not an emergency, the work that got deferred first was often the electrical maintenance that keeps workers safe and equipment running (Koh, 2020). Arc-flash studies went unrenewed, breakers and relays were left untested, thermographic scans were skipped, and preventive maintenance on aging switchgear was pushed to a later date that kept receding (Cai & Luo, 2020). In brownfield facilities, already running on decades-old infrastructure, the consequence was not a single dramatic failure but a slow accumulation: a backlog of deferred maintenance that quietly raised both the danger to workers and the likelihood of electrical failure (Woodhouse, 2014). This study treats that backlog as a measurable risk debt and asks how facilities pay it down. The danger that accumulates in such a backlog is concrete and quantifiable. The most severe electrical hazard to workers is the arc flash, whose thermal energy at a working distance is captured by the incident-energy model that underpins modern electrical-safety analysis, given in Equation (1):

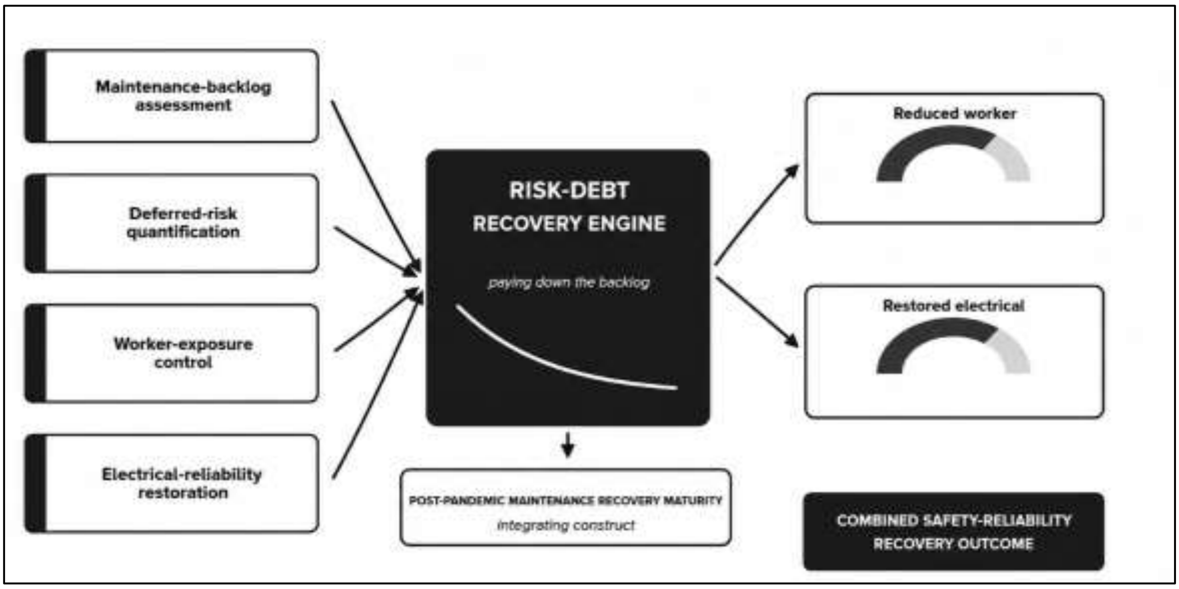
$$E_i = \frac{1}{2} C_f\, V\, I_{\text{arc}}\, t_{\text{arc}} \left(\frac{610^x}{D^x}\right), \qquad E_i\ [\text{cal/cm}^2] \tag{1}$$

Equation (1) expresses the energy a worker would receive as a function of arcing current, arcing time, and distance, and forms the basis of the arc-flash studies that deferred maintenance leaves out of date (IEEE, 2018), (Wilkins et al., 2004). A study whose assumptions no longer match a plant that has since been re-fed, re-fused, or re-configured understates the hazard, so the deferral itself creates exposure (Doughty et al., 2000). The backlog can be described directly: it is a quantity that grows when work is deferred faster than it is cleared, as in Equation (2):

$$B(t) = B_0 + \int_0^t \left(r_{\text{defer}}(\tau) - r_{\text{clear}}(\tau)\right) d\tau \tag{2}$$

Equation (2) expresses the open maintenance backlog at any time as its starting level plus the accumulated difference between the rate at which work is deferred and the rate at which it is cleared (Kobbacy & Murthy, 2008). During the pandemic the deferral rate exceeded the clearance rate for an extended period, so the backlog, and the risk embedded in it, climbed (Chowdhury et al., 2021). Recovery is the process of reversing that inequality until the backlog, and its embedded risk, falls back to a manageable level.

Figure 1: Reducing Worker Exposure and Electrical Failure Risk After COVID-Era Maintenance Delays



The study's central argument is that recovery succeeds or fails not on how much catch-up work a plant does but on how well it targets that work at the risk hidden in the backlog (Abdur & Iftekhar, 2021). A facility that simply resumes its old maintenance calendar clears items in the order they were scheduled, not in the order of the danger they represent, and so spends scarce recovered capacity on low-risk tasks while high-risk exposures wait (Aven, 2016). The alternative is to treat the backlog as a risk debt: to surface every deferred item, estimate the worker-exposure and reliability risk each one carries, and pay the debt down worst-first (Moubray, 1997). Research on maintenance and asset management has long held that intervention should be allocated by consequence rather than by schedule (Rausand, 1998), and the recovery problem makes that principle urgent, because the backlog is finite, the recovered capacity is limited, and the risk is unevenly distributed across the deferred work (ISO, 2014). Three features of the post-pandemic brownfield context make this both necessary and hard. First, the backlog is often poorly documented: records of what was deferred, and when, were themselves a casualty of disrupted operations, so the facility must first recover an accurate picture of its own debt (Remko, 2020). Second, the risk is entangled: the same aging switchgear whose preventive maintenance lapsed is both a worker-exposure hazard and a reliability liability, so recovery work often serves both safety and reliability at once and should be valued accordingly (Brown, 2009). Third, the recovered capacity competes with production pressure to make up lost output, so recovery must be scheduled into scarce outage windows against the same constraints that caused the deferral in the first place (Ivanov, 2020). This study brings these considerations together, framing backlog assessment, risk quantification, exposure control, reliability restoration, and recovery scheduling as components of one capability whose contribution to combined recovery outcomes can be estimated.

Background of the Study

Two bodies of practice meet in this study, and the pandemic forced their intersection. The first is electrical-safety and reliability engineering, which over decades turned the arc-flash hazard into a quantifiable, standardized risk and built rigorous methods for the reliability of industrial power systems (Lee, 1982), (IEEE, 2007). The discipline assumes a maintained system: arc-flash studies kept current, protective devices tested, aging equipment monitored and replaced on schedule (NFPA, 2021). The second is maintenance management, which developed reliability-centered and condition-based approaches for deciding what to maintain, when, and why, on the premise that resources are limited and must be directed where failure matters most (Moubray, 1997), (Mobley, 2002). Each tradition presumed continuity of operations, an assumption the pandemic broke.

The disruption itself has become a subject of study. Research on the pandemic's effect on manufacturing and operations documented widespread deferral of non-urgent activity, workforce constraints, and the accumulation of operational debt that would have to be repaid later (Cai & Luo, 2020), (Kumar et al., 2020), (Paul & Chowdhury, 2021). Parallel work in occupational safety examined how the pandemic strained safety systems and shifted attention away from chronic hazards toward acute infection control (Koh, 2020), (Sinclair et al., 2020). What has not been studied is the specific problem this article addresses: how facilities recover the electrical-maintenance backlog that the pandemic created, and how that recovery affects the twin outcomes of worker exposure and electrical failure risk in brownfield plants (Chowdhury et al., 2021).

A third literature supplies the recovery frame. Resilience engineering and the study of organizational resilience treat a system's capacity to absorb disruption and recover function as a measurable property, not a matter of luck (Hollnagel et al., 2006), (Bhamra et al., 2011). The related work on enterprise and supply-chain resilience showed that recovery is faster and more complete when it is planned, prioritized, and resourced deliberately rather than improvised (Sheffi & Rice, 2005). Applied to maintenance, this suggests that paying down a risk debt is itself a capability that facilities possess in differing degrees, and that the degree, more than the size of the original backlog, may determine how well safety and reliability recover (Teece, 2007).

Problem Statement

The problem this study addresses is that brownfield facilities emerged from the pandemic carrying an electrical-maintenance backlog they cannot clear all at once, and the way they choose to work it down determines how much worker exposure and failure risk they carry in the meantime. A facility that treats recovery as an undifferentiated catch-up, resuming its old schedule and clearing items as capacity allows, leaves high-risk exposures in place while low-risk work is completed, and cannot say how much danger remains at any point (Aven, 2016). Facilities that recover well appear to do so not by having had a smaller backlog but by managing recovery as a measured, risk-prioritized process, which suggests that post-pandemic maintenance recovery maturity, the discipline of running that process, may matter more than the backlog's original size (Teece, 2007).

This matters because the two risks the backlog carries are both serious and often share a cause. An out-of-date arc-flash study or an untested protective device raises the chance that a worker is injured by an arc flash or shock, while lapsed preventive maintenance on aging switchgear raises the chance of an unplanned electrical failure that halts production, and in a brownfield plant the same neglected equipment frequently drives both (Campbell & Dini, 2012). A recovery program that reduces one while ignoring the other, or that cannot demonstrate that either has fallen, leaves risk in place and capacity wasted. The study therefore investigates how a maintenance-recovery capability influences a combined worker-safety and reliability recovery outcome, and how its components, from backlog assessment through risk quantification, exposure control, reliability restoration, and scheduling, shape the results.

Objectives of the Study

The general objective of this study was to assess how a post-pandemic maintenance-recovery capability, integrating backlog assessment, deferred-risk quantification, worker-exposure control, electrical-reliability restoration, and recovery scheduling, influences a combined worker-safety and reliability recovery outcome in brownfield manufacturing facilities. The specific objectives were: to examine the influence of maintenance-backlog assessment on post-pandemic maintenance recovery maturity; to assess the relationship between deferred-risk quantification and the combined recovery outcome; to evaluate the effect of worker-exposure control on the recovery outcome; to determine the role of electrical-reliability restoration in strengthening the outcome; to test the effect of post-pandemic maintenance recovery maturity on the outcome; and to examine the role of recovery scheduling and resourcing in shaping the outcome. A further objective was to gauge recovery maturity and capability gaps across the recovery cycle.

Research Hypotheses

Six hypotheses guided the study. H1 held that maintenance-backlog assessment significantly influences post-pandemic maintenance recovery maturity. H2 held that deferred-risk quantification is significantly and positively related to the combined recovery outcome. H3 held that worker-exposure control significantly influences the recovery outcome. H4 held that electrical-reliability restoration significantly strengthens the recovery outcome. H5 held that post-pandemic maintenance recovery maturity significantly predicts the recovery outcome. H6 held that recovery scheduling and resourcing significantly shapes the recovery outcome.

Significance of the Research

The study speaks to a decision that maintenance, reliability, and safety leaders in brownfield plants faced directly in the pandemic's aftermath: how to work down a dangerous maintenance backlog with limited crews, budget, and outage windows, and how to know whether the effort is reducing the risk that matters (Woodhouse, 2014). By separating the components of a recovery capability and estimating their contributions, it indicates whether the priority should be better backlog visibility, sharper risk quantification, faster exposure control, stronger reliability restoration, or the scheduling and maturity that bind them (Van Horenbeek et al., 2010). Its framing of recovery as paying down a measured risk debt is useful to practitioners who must catch up safely under constraint, and its maturity index and capability priority matrix turn statistical findings into a recovery agenda. For scholarship, the study connects the electrical-safety, maintenance-management, and resilience literatures around a single recovery-capability view, and provides evidence on a problem, the electrical-maintenance debt left by a global disruption, that the literature has not yet examined directly (Bhamra et al., 2011).

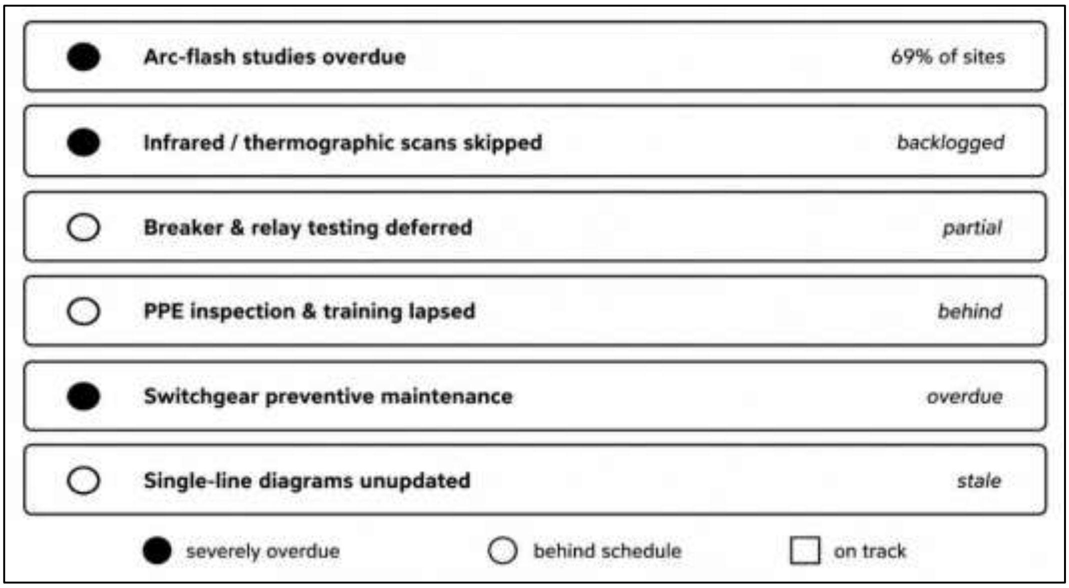
LITERATURE REVIEW

The literature this study draws on spans three fields that rarely met before a global disruption forced them together: electrical-safety and reliability engineering, maintenance management, and the study of organizational resilience and recovery. The review brings them together around one organizing claim, that a pandemic maintenance backlog is a measurable risk debt best paid down worst-first, and moves from the hazards the backlog contains, through the methods for sizing and prioritizing them, to the recovery frame and the theory that unifies the whole. It is selective, following the thread most relevant to the study's argument.

Worker Exposure in Aging Electrical Systems

The most severe electrical hazards to workers are arc flash and shock, and the modern treatment of arc flash rests on recognizing the electric arc as a distinct, quantifiable danger rather than a byproduct of a short circuit (Lee, 1982). Foundational experimental work related arc characteristics to the thermal energy delivered to a nearby worker (Doughty et al., 2000), and this matured into the standardized incident-energy calculations that anchor the arc-flash studies required in industrial facilities (IEEE, 2018). Consensus standards and regulation make those studies, and the protective practices that follow from them, a legal and professional expectation (NFPA, 2021), (OSHA, 2020). Crucially for this study, the protection those studies provide decays when maintenance lapses: incident-energy results depend on protective-device operating times that drift as untested relays and breakers age, and labels and boundaries go stale as a plant is reconfigured (Cawley & Homce, 2010). A deferred arc-flash study is therefore not a neutral delay but an accumulating exposure (Floyd, 2004).

Figure 2: The COVID-Era Maintenance Backlog



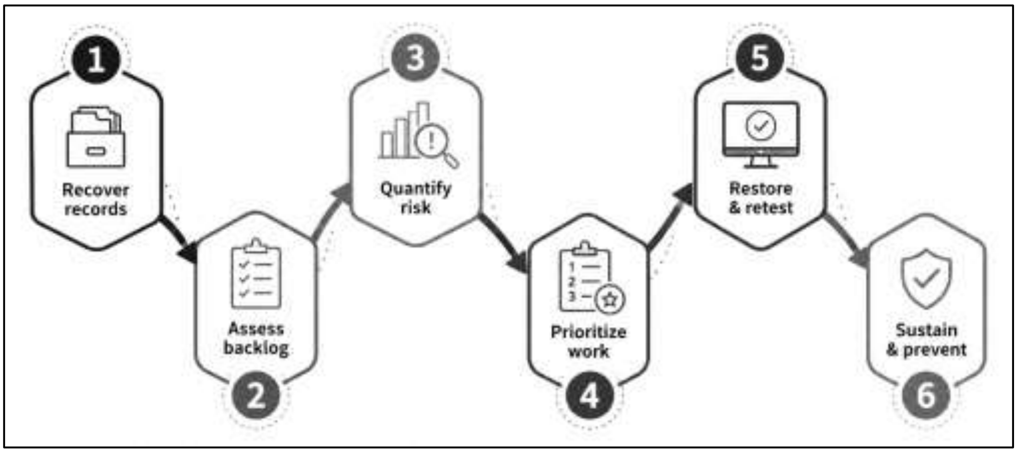
Electrical Reliability and the Cost of Deferral

The second hazard the backlog carries is unreliability. Reliability engineering provides a long tradition of modeling the availability of power systems and quantifying the consequences of interruption (Billinton & Allan, 1992), with industry-specific methods for industrial and commercial power systems (IEEE, 2007). Reliability is expressed in standardized indices for the duration and frequency of interruptions, defined in Equation (3):

$$\mathrm{SAIDI} = \frac{\sum_i r_i N_i}{N_T}, \qquad \mathrm{SAIFI} = \frac{\sum_i N_i}{N_T} \tag{3}$$

Equation (3) defines the system average interruption duration and frequency indices, the standard measures by which distribution reliability is quantified and tracked (Brown, 2009). These indices deteriorate predictably when preventive maintenance is deferred: aging switchgear whose maintenance lapses fails more often and takes longer to restore, so a maintenance backlog translates directly into worsening reliability (Swanson, 2001). Because the same neglected equipment often drives both worker exposure and unreliability, the two risks embedded in the backlog are correlated, and recovery work aimed at one frequently reduces the other (Campbell & Dini, 2012).

Figure 3: Risk-Debt Recovery Pipeline



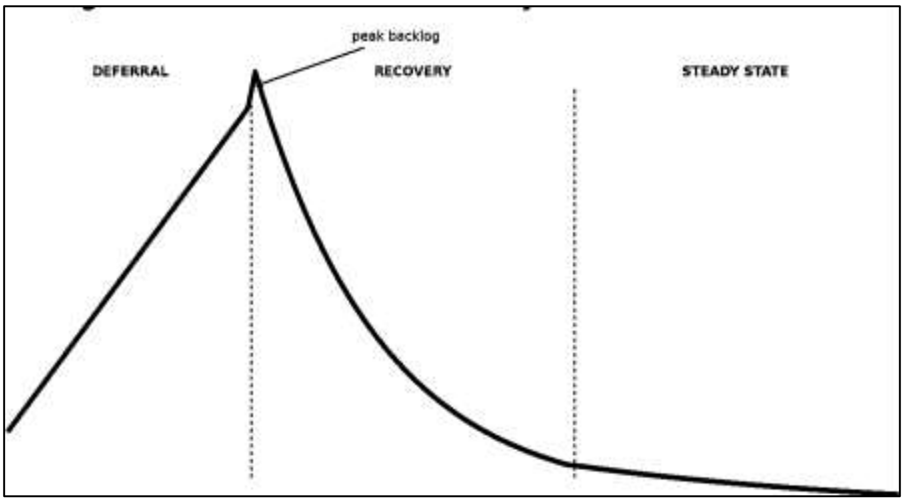
Quantifying the Backlog and Its Embedded Risk

Paying down a risk debt requires first sizing it, which is where maintenance-management research contributes. The maintenance backlog has been studied as a managed quantity, with models of how it accumulates and how it can be worked down under resource constraints (Kobbacy & Murthy, 2008), (Van Horenbeek et al., 2010). But the size of the backlog is not the same as the risk it carries, and the study's premise is that the two must be distinguished. The deferred risk embedded in the backlog can be expressed as a weighted sum over deferred items of the likelihood and severity each carries, as in Equation (4):

$$R_d = \sum_{j=1}^{J} w_j \, p_j \, S_j, \qquad \sum_{j=1}^{J} w_j = 1 \tag{4}$$

Equation (4) expresses deferred risk as a weighted sum across backlog items of the probability that each deferred task's absence leads to harm, times the severity of that harm (Aven, 2016). This reframes recovery from a volume problem, how many items to clear, into a risk problem, which items reduce the most danger per unit of recovered capacity (Boardman et al., 2018). Reliability-centered maintenance provides the logic for making that judgment, allocating limited maintenance effort to the equipment whose failure carries the greatest combined safety and reliability consequence (Moubray, 1997), (Rausand, 1998).

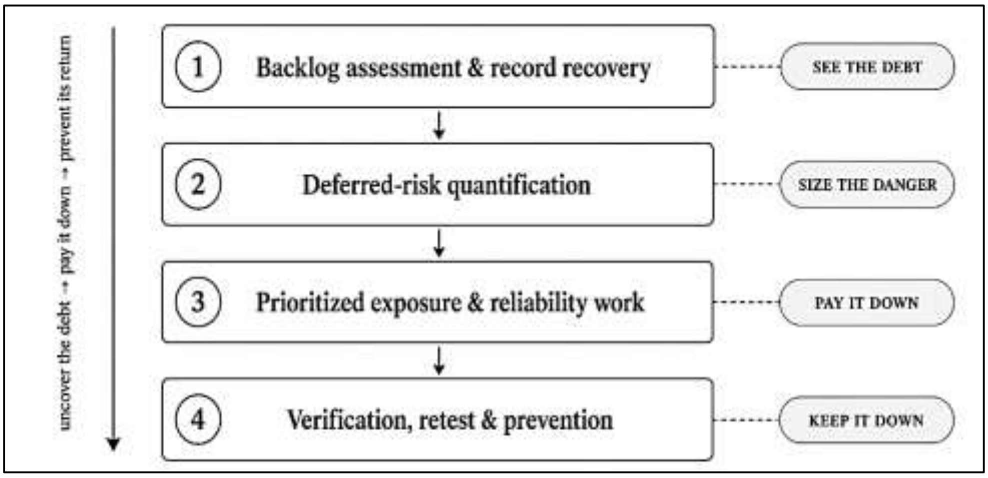
Figure 4: Backlog Burndown Across the Recovery Period



Condition-Based Recovery and Prioritization

Deciding the order of recovery work benefits from condition-based and predictive-maintenance methods, which use the actual state of equipment rather than a fixed calendar to decide what needs attention (Mobley, 2002), (Jardine et al., 2006). After a period of deferral, condition assessment is especially valuable because it reveals which deferred items have degraded into genuine hazards and which remain low-risk, letting a facility recover the record of its own equipment's state before committing scarce capacity (Swanson, 2001). Asset-management frameworks provide the governing structure, treating the aging installed base as a portfolio to be managed against defined objectives and risk tolerances (ISO, 2014), (Amadi-Echendu et al., 2010). Together these approaches answer the recovery problem's central question: given a finite backlog and limited capacity, which work most reduces combined worker-exposure and reliability risk?

Figure 5: Risk-Debt Recovery Capability Stack



Resilience, Recovery, and the Pandemic Disruption

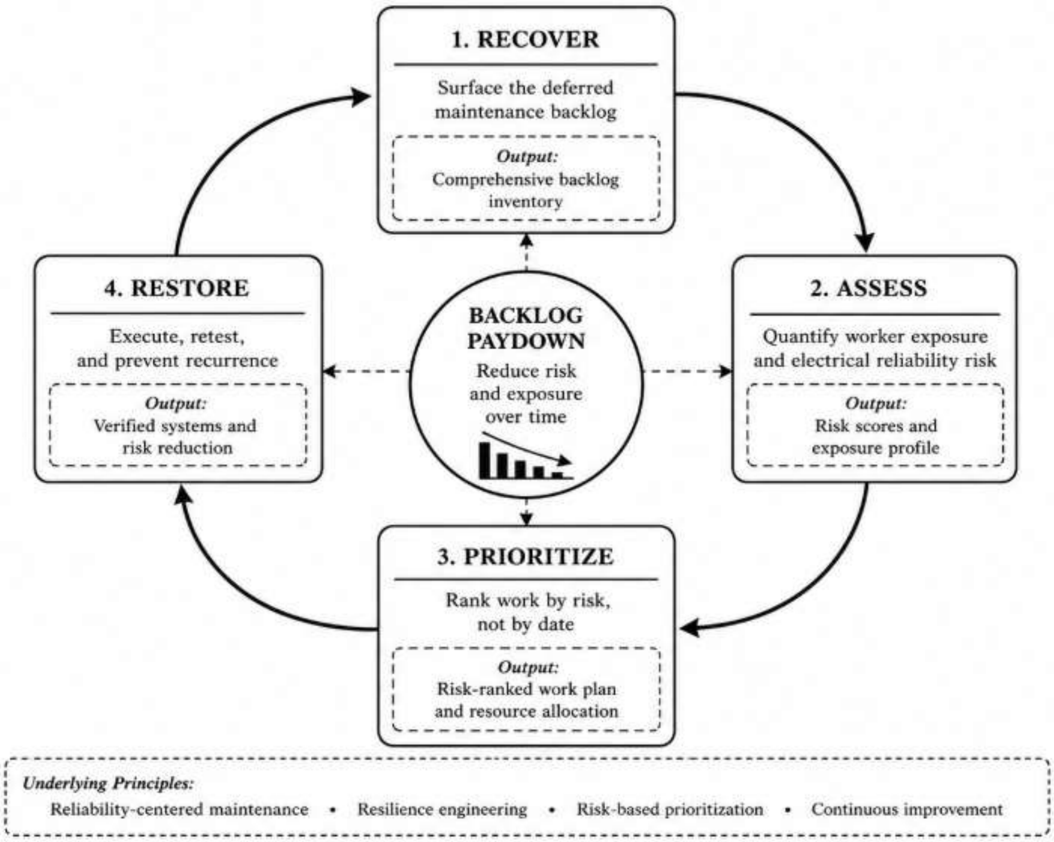
The recovery frame comes from resilience engineering and the study of organizational resilience, which treat a system's capacity to absorb disruption and restore function as a measurable, buildable property (Hollnagel et al., 2006), (Bhamra et al., 2011). Work on enterprise resilience showed that recovery is faster and more complete when planned and prioritized rather than improvised (Sheffi & Rice, 2005), and safety science contributes the recognition that latent conditions, such as deferred maintenance, accumulate silently until a triggering event exposes them (Reason, 1997), (Rasmussen, 1997). The pandemic supplied exactly such a disruption, and research on its operational effects documented widespread deferral and the accumulation of debt to be repaid later (Cai & Luo, 2020), (Kumar et al., 2020), (Paul & Chowdhury, 2021), alongside strain on occupational-safety systems (Koh, 2020), (Sinclair et al., 2020). This study applies the resilience-recovery lens to the specific electrical-maintenance debt that resulted, a problem the literature has documented in aggregate but not examined at the level of how facilities actually pay it down (Chowdhury et al., 2021).

The Recover–Assess–Prioritize–Restore (RAPR) Risk-Recovery Cycle

The capabilities reviewed above are usually pursued separately, but in an effective recovery they form a single managed cycle, and describing that cycle is the study's central theoretical contribution. It proposes the Recover–Assess–Prioritize–Restore (RAPR) risk-recovery cycle: a debt-paydown loop through which a brownfield facility works off its pandemic maintenance backlog. In the recover phase, the facility surfaces the deferred-maintenance backlog and reconstructs an accurate record of what was postponed. In the assess phase, it quantifies the worker-exposure and reliability risk embedded in each deferred item. In the prioritize phase, it ranks the recovery work by risk rather than by date, so that the most dangerous exposures are cleared first. In the restore phase, it executes the work, retests to confirm the hazard has fallen, and feeds the verified result back to reset the backlog baseline and re-rank the remaining work, closing the loop.

The RAPR cycle rests on three theoretical foundations. From reliability-centered maintenance it takes its core logic: that intervention in a constrained system must be allocated by consequence and verified by result, not applied by calendar or assumed to work (Moubray, 1997), (ISO, 2014). From resilience engineering it takes its recovery structure: that restoring function after a disruption is a deliberate, prioritized process whose quality is a measurable organizational capacity, not a matter of simply resuming normal operations (Hollnagel et al., 2006), (Sheffi & Rice, 2005). And from continuous-improvement theory it takes the closed-loop form, in which each cycle of measurement and intervention informs the next and prevents the backlog from silently re-accumulating (Deming, 1986). The integrating construct, post-pandemic maintenance recovery maturity, measures how completely the loop is closed, how rigorously a facility recovers, assesses, prioritizes, and restores as one connected practice (Montgomery, 2009).

Figure 6: The Recover–Assess–Prioritize–Restore (RAPR) Risk-Recovery Cycle



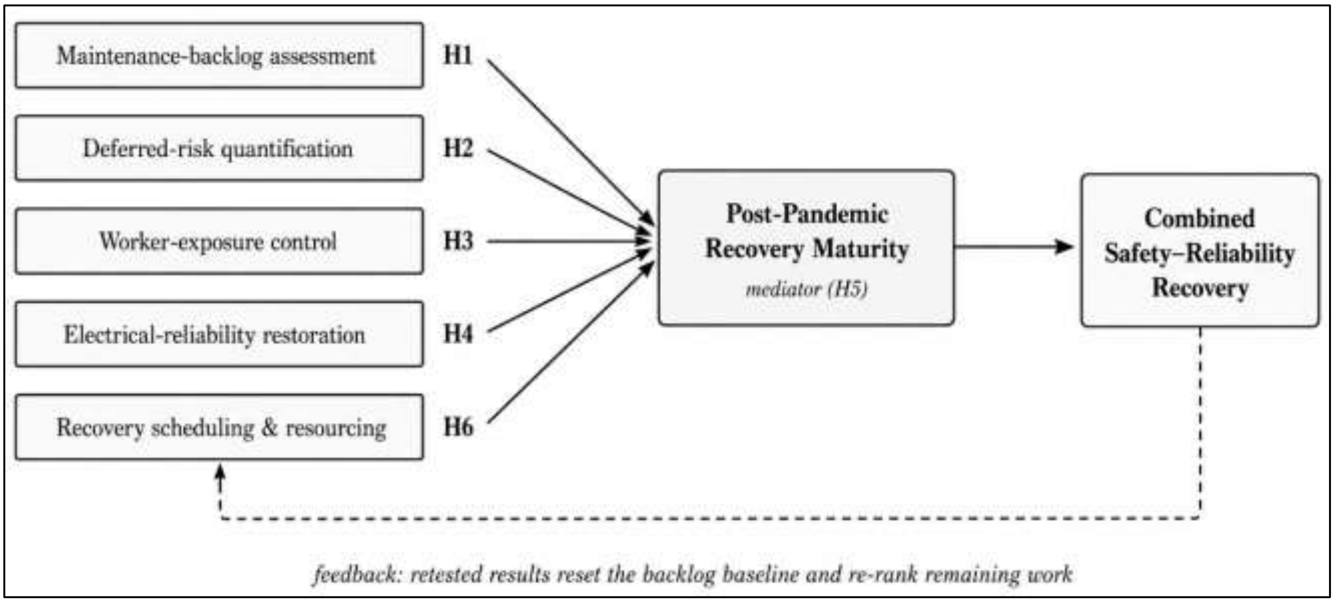
Conceptual Framework

Rendering the RAPR cycle as a testable model, the study positions six capabilities as drivers of the combined safety-reliability recovery outcome, with post-pandemic maintenance recovery maturity acting as the integrating construct through which the others largely operate. Backlog assessment, deferred-risk quantification, worker-exposure control, electrical-reliability restoration, and recovery scheduling each contribute to the outcome, while recovery maturity captures the coherence with which they are combined and is expected to be the strongest single predictor (Teece, 2007). The recovery progress itself can be tracked, expressed as the proportion of the peak backlog that has been paid down and the rate at which it is falling, as in Equation (5):

$$\mathrm{RPI} = 1 - \frac{B(t)}{B_{\text{peak}}}, \qquad v_r = -\frac{dB}{dt} \tag{5}$$

Equation (5) defines a recovery-progress index as the share of the peak backlog now cleared, and a recovery velocity as the rate at which the backlog is falling (Kobbacy & Murthy, 2008). The conceptual model, shown in Figure 7, includes a feedback path from restored, retested outcomes back to backlog assessment and prioritization, reflecting the closed-loop logic of the recovery cycle and distinguishing it from a one-time catch-up in which work is cleared and never re-evaluated (Deming, 1986).

Figure 7: Conceptual Model for Combined Safety–Reliability Recovery



METHODS

Research Design

The study used a quantitative, cross-sectional survey design, appropriate for measuring perceptions of a maintenance-recovery capability across a defined population at one point in time and for testing hypothesized relationships among latent constructs (Venkatesh et al., 2003). A survey strategy fit the aim because the constructs, backlog assessment, deferred-risk quantification, worker-exposure control, reliability restoration, recovery scheduling, recovery maturity, and the combined recovery outcome, are best judged by the engineers, planners, and managers who actually assessed, prioritized, and worked down the pandemic backlog in their plants. The design favors comparability across many respondents over the depth of a single facility, allowing the relative contribution of each capability to be estimated (Hair et al., 2019).

Population and Sampling

The target population comprised professionals who managed electrical maintenance and safety in brownfield manufacturing facilities through the pandemic and its aftermath. A purposive sampling strategy reached respondents with direct, informed exposure to the recovery problem, appropriate when the aim is expert assessment rather than broad generalization (Venkatesh et al., 2003). Of 172 questionnaires distributed, 163 were returned and 154 were retained after screening for completeness and engagement, a valid response rate of 89.5%. The sample spanned maintenance and reliability engineers, electrical and power engineers, EHS and safety managers, plant and facilities managers, and maintenance planners, with 70.1% reporting direct involvement in managing electrical maintenance or safety through the pandemic period.

Table 1: Response Rate Summary

Category	Count	Percentage
Distributed	172	100.0%
Returned	163	94.8%
Valid and used	154	89.5%
Excluded after screening	9	5.2%

Table 2: Respondent Demographics (n = 154)

Characteristic	Category	n	%
Role	Maintenance & reliability engineers	40	26.0%
	Electrical / power engineers	34	22.1%
	EHS / safety managers	31	20.1%
	Plant / facilities managers	27	17.5%
	Maintenance planners / schedulers	22	14.3%
Experience	1–5 years	26	16.9%
	6–15 years	63	40.9%
	More than 15 years	65	42.2%

Instrument and Measures

Data were collected with a structured questionnaire measuring seven constructs on five-point Likert scales anchored from strongly disagree to strongly agree. Items were adapted from established instruments in electrical safety, reliability and maintenance management, resilience, and information-systems success research, then refined for the post-pandemic recovery context (DeLone & McLean, 2003), (Van Horenbeek et al., 2010). The seven constructs were maintenance-backlog assessment, deferred-risk quantification, worker-exposure control, electrical-reliability restoration, recovery scheduling and resourcing, post-pandemic maintenance recovery maturity, and the combined worker-safety and reliability recovery outcome. Content validity was established by expert review, and a pilot with a small group of practitioners confirmed clarity and internal consistency before full deployment (Venkatesh et al., 2003).

DATA ANALYSIS

Analytical Approach

Analysis proceeded in stages: descriptive statistics summarized the level of each construct; Cronbach's alpha assessed internal-consistency reliability; Pearson correlations examined bivariate relationships; and multiple linear regression estimated the joint contribution of the capabilities to the combined recovery outcome (Hair et al., 2019). A maturity index and a capability priority matrix then translated the statistics into practical terms. The integrating construct, post-pandemic maintenance recovery maturity, was constructed as a weighted mean of its component capabilities, as in Equation (6):

$$\mathrm{PMR} = \sum_{c=1}^{C} w_c \bar{x}_c, \qquad \sum_{c=1}^{C} w_c = 1, \quad w_c \geq 0 \tag{6}$$

Equation (6) aggregates the constituent capability scores into a single maturity measure, with weights summing to one (Van Horenbeek et al., 2010). Reliability was quantified with coefficient alpha, given in Equation (7):

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_i^2}{\sigma_T^2}\right) \tag{7}$$

In Equation (7), K is the number of items, the numerator sums item variances, and the denominator is the variance of the total score; values at or above 0.70 indicate acceptable reliability (DeLone & McLean, 2003). The central test of the study's model used multiple regression, specified in Equation (8):

$$\mathrm{RO} = \beta_0 + \sum_{k=1}^{6} \beta_k X_k + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \sigma^2) \tag{8}$$

Equation (8) regresses the combined safety-reliability recovery outcome on the six capability predictors, with standardized coefficients indicating the relative strength of each (Boardman et al., 2018). The assumptions of linear regression, linearity, independence, homoscedasticity, and approximate normality of residuals, were checked before interpretation (Hair et al., 2019).

Descriptive Statistics

Table 3 reports the mean and standard deviation of each construct. All seven fell in the high band, indicating that respondents generally regarded their recovery capabilities as strong, with meaningful variation. The combined safety-reliability recovery outcome recorded the highest mean at 4.29, and maintenance-backlog assessment the lowest at 3.92, a pattern consistent with the study's argument that the foundational work of accurately surfacing the backlog, disrupted records and all, is often the least complete even where the recovery outcome is valued (Remko, 2020).

Table 3: Descriptive Statistics of Study Variables

Variable	Mean	SD
Combined safety–reliability recovery	4.29	0.50
Worker-exposure control	4.20	0.53
Post-pandemic recovery maturity	4.13	0.55
Electrical-reliability restoration	4.08	0.58
Deferred-risk quantification	4.03	0.61
Recovery scheduling & resourcing	3.97	0.63
Maintenance-backlog assessment	3.92	0.66

Reliability Analysis

Table 4 presents reliability coefficients. All constructs exceeded the 0.70 threshold, with alpha ranging from 0.83 to 0.94, indicating good to excellent internal consistency and supporting the use of the scales in subsequent analysis (DeLone & McLean, 2003). The high reliability of the recovery-outcome and maturity scales is particularly important, since these anchor the study's central relationship.

Table 4: Reliability Analysis of Study Constructs

Construct	Items	Cronbach's Alpha	Decision
Combined safety–reliability recovery	6	0.94	Reliable
Post-pandemic recovery maturity	6	0.92	Reliable
Worker-exposure control	5	0.90	Reliable
Electrical-reliability restoration	6	0.89	Reliable
Deferred-risk quantification	5	0.87	Reliable
Recovery scheduling & resourcing	5	0.85	Reliable
Maintenance-backlog assessment	6	0.83	Reliable

Correlation Analysis

Table 5 reports Pearson correlations among the constructs. All were positive and statistically significant, consistent with an integrated recovery system in which the capabilities move together (Bhamra et al., 2011). The strongest association was between post-pandemic maintenance recovery maturity and the combined recovery outcome, r = 0.80, followed by the correlation between worker-exposure control and the outcome, r = 0.72. The prominence of maturity in the correlation structure foreshadows its role as the leading predictor in the regression.

Table 5: Correlation Matrix of Study Variables

Variable	Back.	D-risk	Expo.	Rest.	Sched.	Matur.	Recov.
Backlog assessment	1.00						
Deferred-risk quantification	0.58	1.00					
Worker-exposure control	0.55	0.61	1.00				
Reliability restoration	0.56	0.60	0.62	1.00			
Recovery scheduling	0.57	0.59	0.58	0.60	1.00		
Recovery maturity	0.68	0.69	0.70	0.67	0.66	1.00	
Combined recovery outcome	0.62	0.71	0.72	0.69	0.68	0.80	1.00

Regression Analysis

Table 6 reports the regression model summary and Table 7 the coefficients. The six capabilities jointly explained 74.9% of the variance in the combined recovery outcome, $R^2 = 0.749$, adjusted $R^2 = 0.739$, and the model was highly significant, $F(6,147) = 73.15$, $p < 0.001$ (Boardman et al., 2018). Post-pandemic maintenance recovery maturity was the strongest predictor, $\beta = 0.32$, followed by worker-exposure control, $\beta = 0.25$, and electrical-reliability restoration, $\beta = 0.20$; deferred-risk quantification, recovery scheduling, and backlog assessment were significant but smaller contributors. The dominance of maturity supports the study's core claim that running the recovery as a coherent, measured process, more than any single component, drives the combined outcome.

Table 6: Regression Model Summary

Statistic	Value
R	0.865
R^2	0.749
Adjusted R^2	0.739
Std. error of estimate	0.264
F (6, 147)	73.15
Significance (p)	< 0.001

Table 7: Regression Coefficients

Predictor	β	t	p
Post-pandemic recovery maturity	0.32	5.02	< 0.001
Worker-exposure control	0.25	3.90	< 0.001
Electrical-reliability restoration	0.20	3.20	0.002
Deferred-risk quantification	0.18	2.86	0.005
Recovery scheduling & resourcing	0.14	2.42	0.017
Maintenance-backlog assessment	0.12	2.15	0.033

HYPOTHESIS TESTING

The six hypotheses were evaluated using the regression results together with the correlation evidence. Table 8 summarizes the outcome. All six were supported: each capability was significantly and positively associated with its hypothesized outcome, and post-pandemic maintenance recovery maturity's effect on the combined outcome was both significant and the largest in the model, consistent with its theorized role as the integrating construct that closes the recovery loop (Teece, 2007).

Table 8: Summary of Hypothesis Testing

Hypothesis	Path	β / r	Result
H1	Backlog assessment → recovery maturity	r = 0.68	Supported
H2	Deferred-risk quantification → recovery outcome	β = 0.18	Supported
H3	Worker-exposure control → recovery outcome	β = 0.25	Supported
H4	Reliability restoration → recovery outcome	β = 0.20	Supported
H5	Recovery maturity → recovery outcome	β = 0.32	Supported
H6	Recovery scheduling → recovery outcome	β = 0.14	Supported

POST-PANDEMIC RECOVERY MATURITY ANALYSIS

To turn the constructs into a practical diagnostic, the study computed a maturity index across the stages of the recovery cycle. The index is the mean of stage-level maturity scores, and the accompanying gap measure contrasts the importance and current effectiveness of each capability area, as in Equation (9):

$$\mathrm{MI} = \frac{1}{S}\sum_{s=1}^{S} \bar{m}_s, \qquad \mathrm{Gap}_a = \bar{I}_a - \bar{E}_a \tag{9}$$

In Equation (9), the maturity index averages maturity across the cycle stages, while the gap for each capability area is the difference between its rated importance and its rated effectiveness (Montgomery, 2009). Table 9 reports maturity by stage. The overall index was 4.07, indicating generally mature recovery capabilities, with exposure control and verification relatively strong and backlog assessment, scheduling, and prevention comparatively weaker, a profile consistent with facilities that execute and confirm individual recovery work well but are less disciplined about surfacing the full backlog, resourcing the recovery, and preventing the debt from re-accumulating (Remko, 2020).

Table 9: Post-Pandemic Recovery Maturity by Cycle Stage

Cycle Stage	Maturity (1–5)	Level
Worker-exposure control	4.15	High
Verification & retest	4.11	High
Deferred-risk quantification	4.10	High
Reliability restoration	4.07	High
Backlog assessment	4.04	High
Scheduling & resourcing	4.02	High
Prevention & governance	4.00	Moderate–High

RECOVERY CAPABILITY PRIORITY MATRIX

The priority matrix places each capability area according to its importance and its current effectiveness, so that the widest gaps, areas rated important but not yet effective, rise to the top of the recovery agenda (Van Horenbeek et al., 2010). Table 10 reports the results, ordered by gap. The largest gaps appeared in clearing overdue arc-flash studies, completing deferred breaker and relay testing, and catching up skipped thermographic inspection, indicating that respondents most wanted to close out the specific deferred items that carry the greatest worker-exposure and reliability risk. These priorities map cleanly onto the RAPR cycle: they concentrate in the assess and restore phases, where deferred hazards are sized and actually cleared (Moubray, 1997).

Table 10: Recovery Capability Priority Matrix

Capability Area	Importance	Effectiveness	Gap	Priority
Overdue arc-flash study clearance	4.75	3.63	1.12	Very High
Deferred breaker & relay testing	4.69	3.60	1.09	Very High
Skipped thermographic inspection	4.66	3.61	1.05	Very High
Recovery crew & outage resourcing	4.58	3.55	1.03	High
Backlog record recovery	4.60	3.70	0.90	High
Risk-based work prioritization	4.56	3.67	0.89	High
Lapsed PPE & training	4.44	3.80	0.64	Moderate
Preventive-maintenance restart	4.42	3.82	0.60	Moderate

FINDINGS

Assembled, the results tell a consistent story. First, respondents regard their recovery capabilities as broadly strong: every construct sat in the high band, with the combined recovery outcome and worker-exposure control at the top. Second, the capabilities are tightly interrelated, all correlations were positive and significant, as one expects if they are components of a single recovery process rather than independent activities (Bhamra et al., 2011). Third, and most importantly, the capabilities jointly explain a large share of the variance in the combined recovery outcome, 74.9%, and post-pandemic maintenance recovery maturity is the strongest single predictor, ahead of worker-exposure control and reliability restoration. Fourth, the maturity and priority analyses locate where the capabilities are strongest and weakest. Maturity is highest in exposure control and verification and lowest in backlog assessment, scheduling, and prevention, while the widest capability gaps lie in clearing overdue arc-flash studies, completing deferred breaker and relay testing, and catching up skipped thermographic inspection. The consistent implication is that the frontier of improvement is not more recovery activity in general but a more complete recovery loop, accurate backlog visibility, risk-based prioritization, and prevention of re-accumulation (Aven, 2016). This is exactly what the RAPR framework predicts: safety and reliability recover together when the recover, assess, prioritize, and restore phases reinforce one another, and the greatest returns come from strengthening the phases that surface the full backlog and confirm that the most dangerous deferred work has actually been cleared. The joint treatment of worker exposure and reliability is central to the reading: because the same aging, maintenance-starved switchgear drives both the arc-flash hazard and the reliability liability, and because the same recovery work reduces both, the two outcomes recover together rather than competing, which is why respondents rated the combined outcome so highly and why recovery maturity, the discipline of running the whole loop, predicts it best (Campbell & Dini, 2012).

DISCUSSION

The results support the study's central proposition: that safety and reliability recover together, and stay recovered, only when a facility treats its pandemic maintenance backlog as a measured risk debt to be worked down deliberately. The dominance of post-pandemic maintenance recovery maturity as a predictor, $\beta = 0.32$, is the clearest expression of this. Read through the Recover–Assess–Prioritize–Restore cycle, maturity measures how completely a facility recovers, assesses, prioritizes, and restores as one connected practice, so its strength as a predictor reflects the framework's premise that the combined recovery outcome emerges from the coherence of the whole loop rather than from any single phase (Teece, 2007). The strong effect of worker-exposure control, $\beta = 0.25$, the second-largest, confirms that the direct reduction of worker danger, clearing overdue arc-flash studies, restoring protective-device integrity, reinstating safe-work practices, is the core of what recovery is for (Cawley & Homce, 2010). Yet the priority analysis is revealing, because respondents rated exposure control highly while flagging overdue arc-flash study clearance and deferred breaker and relay testing as their largest capability gaps. This suggests that the constraint is not knowing what to do but completing the specific deferred items that carry the most risk, under the same capacity limits that caused the deferral (Floyd, 2004). The significant effect of electrical-reliability restoration, $\beta = 0.20$, confirms the study's premise that the backlog carries two correlated risks, and that recovery work on aging switchgear reduces both worker exposure and failure risk at once, so the two outcomes need not be traded against each other (Campbell & Dini, 2012).

The significant contribution of deferred-risk quantification, $\beta = 0.18$, together with the foundational role of backlog assessment, its strong correlation with maturity, $r = 0.68$, and significant regression effect, $\beta = 0.12$, confirms that effective recovery rests on first seeing the debt clearly and sizing the danger within it. That backlog assessment recorded the lowest mean of any construct, 3.92, while remaining a significant driver and carrying a substantial capability gap, mirrors a genuine difficulty of the post-pandemic moment: the records of what was deferred, and when, were themselves disrupted, so reconstructing an accurate backlog is hard, yet everything downstream, risk sizing, prioritization, and verified recovery, depends on it (Remko, 2020). Facilities appear to recognize accurate backlog assessment as both essential and incomplete, which is precisely the profile of a foundational capability warranting renewed investment (ISO, 2014).

The significant effect of recovery scheduling and resourcing, $\beta = 0.14$, though the smallest, reinforces the framework's logic: risk-based priorities matter only if the facility can secure the crews and outage windows to act on them, and that scheduling competes with production pressure to recover lost output (Ivanov, 2020). The comparatively lower maturity of backlog assessment, scheduling, and prevention, and the persistence of gaps in clearing the most dangerous deferred work, together sketch a clear pattern: facilities are relatively strong at executing and verifying recovery work but weaker at the ends of the cycle, surfacing the full backlog before and preventing its re-accumulation after (Deming, 1986). This is the imbalance the RAPR framework warns against, because a recovery loop with weak ends can clear visible work while unseen debt persists and new debt quietly builds. Crucially, the study's central premise, that worker exposure and reliability should be recovered jointly, is borne out: respondents rated the combined outcome highest of all constructs, and recovery maturity, the discipline of running the joint loop, predicted it most strongly, indicating that treating the two risks as one debt to be paid down together is not merely tidy but effective (Brown, 2009). The efficiency argument follows directly: because the same neglected switchgear poses both an arc-flash hazard and a reliability liability, a single recovery intervention often reduces both, so a joint recovery program extracts more risk reduction from each scarce outage window than separate safety and reliability catch-ups would (Billinton & Allan, 1992).

CONCLUSION

This study set out to assess how a post-pandemic maintenance-recovery capability, understood as an integrated process, influences a combined worker-safety and reliability recovery outcome in brownfield manufacturing facilities. Using a quantitative, cross-sectional design and responses from 154 maintenance, electrical, and safety professionals, it found that all six hypothesized relationships held and that the capabilities together explained 74.9% of the variance in the combined recovery outcome. Post-pandemic maintenance recovery maturity emerged as the strongest predictor, underscoring that the discipline of running a complete, risk-prioritized recovery matters more than any single element. Worker-exposure control and electrical-reliability restoration followed, while deferred-risk quantification, recovery scheduling, and backlog assessment were significant but smaller contributors.

The study concludes that the electrical-maintenance backlog left by the pandemic is best understood not as a queue of overdue tasks to be cleared as capacity allows but as a measured risk debt to be paid down deliberately. The Recover–Assess–Prioritize–Restore cycle offers a way to manage that debt: a facility surfaces the backlog, sizes the worker-exposure and reliability risk within it, ranks the work by risk rather than by date, and restores and retests, feeding verified results back to re-rank what remains. Combined outcomes rise when these phases reinforce one another, and the evidence here indicates that the phases most in need of strengthening are the ends of the cycle, accurate backlog assessment before and prevention of re-accumulation after, rather than the execution in the middle. Importantly, the study finds that worker exposure and reliability recover together rather than competing: because the same aging, maintenance-starved infrastructure drives both, the same recovery work improves both, and a joint program uses scarce recovery capacity more efficiently than separate efforts. For facilities, the practical message is to run recovery as one measured, risk-prioritized loop rather than as an undifferentiated catch-up; for scholarship, the study shows the value of joining the electrical-safety, maintenance-management, and resilience literatures around a single recovery-capability view of a problem, the maintenance debt left by a global disruption, that the literature has documented but not examined at this level.

RECOMMENDATIONS

Several recommendations follow from the findings. First, facilities should invest in surfacing the backlog accurately, treating the reconstruction of a complete, current record of deferred electrical maintenance as a first-order activity, since backlog assessment was both the lowest-rated capability and the foundation on which risk sizing, prioritization, and verified recovery all depend. Second, they should quantify the risk embedded in the backlog and prioritize recovery work by that risk rather than by the date each item was originally scheduled, so that the most dangerous deferred exposures are cleared first.

Third, facilities should close the loop through verification, retesting after each recovery intervention to confirm that the specific hazard, an out-of-date arc-flash study, an untested breaker, has actually been reduced, since worker-exposure control was among the strongest predictors and the widest gaps concerned clearing exactly those items. Fourth, they should pursue worker safety and reliability jointly, using the fact that the same aging switchgear drives both to select recovery work that reduces both and thereby extract more risk reduction from each scarce outage window. Fifth, they should resource the recovery realistically, securing the crews and outage windows that risk-based priorities require against competing production pressure. Finally, facilities should prevent re-accumulation by managing recovery as a sustained capability, using a maturity assessment and a capability priority matrix to direct effort toward the weakest phases of the Recover–Assess–Prioritize–Restore cycle, typically backlog visibility and prevention, and building the always-ready maintenance discipline that keeps a new backlog from silently forming.

LIMITATIONS OF THE STUDY

This study has several limitations. First, the cross-sectional design captured perceptions at a single point in the recovery and cannot establish causal direction or track how the backlog and its risks actually fell over time; a longitudinal design would allow stronger causal inference and directly capture the burndown dynamics central to the RAPR framework. Second, the study relied on perceptual, self-reported measures completed by professionals, so the results reflect informed assessment rather than objective measurement of backlog size, incident energy, reliability indices, or injury and outage rates; future work could pair perception data with hard metrics such as open work-order counts, calculated incident energy, measured SAIDI and SAIFI, recordable injury rates, and downtime hours. Third, the purposive sample, while appropriate for reaching knowledgeable respondents, limits generalizability to the broader population of brownfield facilities, which varied widely in how severely the pandemic disrupted their operations. Fourth, the constructs were assessed at a general level, and the relative importance of specific capabilities may differ across industries, plant ages, and the depth of the original deferral. Finally, the study did not directly measure the capital cost or return on investment of the recovery work, which is a decisive practical consideration under post-pandemic budget constraints and a promising avenue for future research.

REFERENCES

[1]. Amadi-Echendu, J. E., Brown, K., Willett, R., & Mathew, J. (Eds.). (2010). Definitions, concepts and scope of engineering asset management. Springer. https://doi.org/10.1007/978-1-84996-178-3

[2]. Aven, T. (2016). Risk assessment and risk management: Review of recent advances on their foundation. European Journal of Operational Research, 253(1), 1–13. https://doi.org/10.1016/j.ejor.2015.12.023

[3]. Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: The concept, a literature review and future directions. International Journal of Production Research, 49(18), 5375–5393. https://doi.org/10.1080/00207543.2011.563826

[4]. Billinton, R., & Allan, R. N. (1992). Reliability evaluation of engineering systems: Concepts and techniques (2nd ed.). Springer. https://doi.org/10.1007/978-1-4899-1860-4

[5]. Boardman, A. E., Greenberg, D. H., Vining, A. R., & Weimer, D. L. (2018). Cost-benefit analysis: Concepts and practice (5th ed.). Cambridge University Press. https://doi.org/10.1017/9781108235594

[6]. Brown, R. E. (2009). Electric power distribution reliability (2nd ed.). CRC Press. https://doi.org/10.1201/9781420067194

[7]. Cai, M., & Luo, J. (2020). Influence of COVID-19 on manufacturing industry and corresponding countermeasures from supply chain perspective. Journal of Shanghai Jiaotong University (Science), 25, 409–416. https://doi.org/10.1080/00207543.2020.1785034

[8]. Campbell, R. B., & Dini, D. A. (2012). Occupational injuries from electrical shock and arc flash events. IEEE Industry Applications Magazine, 18(4), 50–58. https://doi.org/10.1109/MIAS.2012.2210043

[9]. Cawley, J. C., & Homce, G. T. (2010). Trends in electrical injury in the U.S., 1992–2002. IEEE Transactions on Industry Applications, 46(3), 1223–1230. https://doi.org/10.1109/TIA.2010.2049768

[10]. Chowdhury, P., Paul, S. K., Kaisar, S., & Moktadir, M. A. (2021). COVID-19 pandemic related supply chain studies: A systematic review. Journal of Business Research, 148, 375–392. https://doi.org/10.1016/j.jbusres.2021.02.026

[11]. DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

[12]. Deming, W. E. (1986). Out of the crisis. MIT Press. https://doi.org/10.7551/mitpress/11090.001.0001

[13]. Doughty, R. L., Neal, T. E., Dear, T. A., & Bingham, A. H. (2000). Testing update on protective clothing and equipment for electric arc exposure. IEEE Industry Applications Magazine, 6(1), 37–49. https://doi.org/10.1109/28.847021

[14]. Floyd, H. L. (2004). A controls approach for electrical safety. IEEE Industry Applications Magazine, 10(3), 26–31. https://doi.org/10.1109/MIA.2004.1275462

[15]. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage. https://doi.org/10.1002/9781119409137

[16]. Hollnagel, E., Woods, D. D., & Leveson, N. (Eds.). (2006). Resilience engineering: Concepts and precepts. Ashgate. https://doi.org/10.1201/9781315605685

[17]. International Organization for Standardization. (2014). ISO 55000: Asset management — Overview, principles and terminology. ISO. https://www.iso.org/standard/55088.html

[18]. IEEE. (2007). IEEE recommended practice for the design of reliable industrial and commercial power systems (IEEE Std 493-2007, Gold Book). IEEE. https://doi.org/10.1109/IEEESTD.2007.380668

[19]. IEEE. (2018). IEEE guide for performing arc-flash hazard calculations (IEEE Std 1584-2018). IEEE. https://doi.org/10.1109/IEEESTD.2018.8563139

[20]. Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis of the COVID-19 outbreak. Transportation Research Part E, 136, 101922. https://doi.org/10.1016/j.tre.2020.101922

[21]. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

[22]. Kobbacy, K. A. H., & Murthy, D. N. P. (Eds.). (2008). Complex system maintenance handbook. Springer. https://doi.org/10.1007/978-1-84800-011-7

[23]. Koh, D. (2020). Occupational risks for COVID-19 infection. Occupational Medicine, 70(1), 3–5. https://doi.org/10.1093/occmed/kqaa036

[24]. Kumar, A., Luthra, S., Mangla, S. K., & Kazançoglu, Y. (2020). COVID-19 impact on sustainable production and operations management. Sustainable Operations and Computers, 1, 1–7. https://doi.org/10.1080/00207543.2020.1792000

[25]. Lee, R. H. (1982). The other electrical hazard: Electric arc blast burns. IEEE Transactions on Industry Applications, IA-18(3), 246–251. https://doi.org/10.1109/TIA.1982.4504092

[26]. Mobley, R. K. (2002). An introduction to predictive maintenance (2nd ed.). Butterworth-Heinemann. https://doi.org/10.1016/B978-0-7506-7531-4.X5000-3

[27]. Montgomery, D. C. (2009). Introduction to statistical quality control (6th ed.). Wiley. https://www.wiley.com/en-us/Introduction+to+Statistical+Quality+Control%2C+7th+Edition-p-9781118146811

[28]. Moubray, J. (1997). Reliability-centered maintenance (2nd ed.). Industrial Press. https://www.worldcat.org/title/reliability-centered-maintenance/oclc/36130249

[29]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387

[30]. National Fire Protection Association. (2021). NFPA 70E: Standard for electrical safety in the workplace. NFPA. https://www.nfpa.org/codes-and-standards/nfpa-70e-standard-development/70e

[31]. Occupational Safety and Health Administration. (2020). Electric power generation, transmission, and distribution (29 CFR 1910.269). U.S. Department of Labor. https://www.osha.gov/laws-regs/regulations/standardnumber/1910/1910.269

[32]. Paul, S. K., & Chowdhury, P. (2021). A production recovery plan in manufacturing supply chains for a high-demand item during COVID-19. International Journal of Physical Distribution & Logistics Management, 51(2), 104–125. https://doi.org/10.1108/IJPDLM-04-2020-0127

[33]. Rasmussen, J. (1997). Risk management in a dynamic society: A modelling problem. Safety Science, 27(2–3), 183–213. https://doi.org/10.1016/S0925-7535(97)00052-0

[34]. Rausand, M. (1998). Reliability-centered maintenance. Reliability Engineering & System Safety, 60(2), 121–132. https://doi.org/10.1016/S0951-8320(98)00005-4

[35]. Reason, J. (1997). Managing the risks of organizational accidents. Ashgate. https://doi.org/10.4324/9781315543543

[36]. Remko, van H. (2020). Research opportunities for a more resilient post-COVID-19 supply chain. International Journal of Operations & Production Management, 40(4), 341–355. https://doi.org/10.1108/IJOPM-03-2020-0165

[37]. Sheffi, Y., & Rice, J. B. (2005). A supply chain view of the resilient enterprise. MIT Sloan Management Review, 47(1), 41–48. https://sloanreview.mit.edu/article/a-supply-chain-view-of-the-resilient-enterprise/

[38]. Sinclair, R. R., Allen, T., Barber, L., Bergman, M., Britt, T., Butler, A., … Yuan, Z. (2020). Occupational health science in the time of COVID-19. Occupational Health Science, 4, 1–22. https://doi.org/10.1037/ocp0000191

[39]. Swanson, L. (2001). Linking maintenance strategies to performance. International Journal of Production Economics, 70(3), 237–244. https://doi.org/10.1016/S0925-5273(00)00156-6

[40]. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

[41]. Van Horenbeek, A., Pintelon, L., & Muchiri, P. (2010). Maintenance optimization models and criteria. International Journal of System Assurance Engineering and Management, 1, 189–200. https://doi.org/10.1007/s10845-010-0406-3

[42]. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

[43]. Wilkins, R., Allison, M., & Lang, M. (2004). Improved method for arc flash hazard analysis. Proceedings of the IEEE Industry Applications Society Annual Meeting, 55–62. https://doi.org/10.1109/IAS.2004.1348530

[44]. Woodhouse, J. (2014). Asset management: Concepts and practices. Institution of Engineering and Technology. https://doi.org/10.1049/pe:20060505