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# Impact of Predictive Arc-Flash Mitigation on Safety, Downtime, and Retrofit Efficiency in U.S. Manufacturing Power Systems

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## Abstract
*An arc flash releases its energy in milliseconds, a burst of heat, light, and pressure that can injure a worker standing at an electrical panel before a conventional protective device has finished deciding to trip. In U.S. manufacturing plants, where aging switchgear sits close to people and production alike, this split-second hazard has long been managed reactively, through protective equipment worn in case the worst happens and periodic studies filed and shelved. This study examines a different posture: predictive arc-flash mitigation, in which sensing, diagnostics, and fast adaptive protection work together to anticipate and clear a fault before it becomes an injury. Rather than asking whether one relay or sensor performs, the study asks what makes a plant's whole predictive-mitigation capability effective across three outcomes that plant managers weigh together, worker safety, production downtime, and the efficiency of retrofitting older systems. It models worker safety outcome effectiveness as a function of six capabilities: arc-flash hazard characterization and incident-energy modeling, predictive fault sensing and diagnostics, adaptive protection and fast tripping, retrofit design and integration efficiency, downtime and operational-continuity impact, and an integrating construct of predictive mitigation maturity. Evidence came from a structured five-point Likert survey completed by 152 valid respondents out of 170 distributed, an 89.4% valid response rate, drawn from electrical and power engineers, plant maintenance and reliability staff, EHS and safety managers, protection and controls specialists, and facilities managers, of whom 69.1% worked directly with power-system protection or plant electrical safety. 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 worker safety outcome effectiveness at a mean of 4.28 and adaptive protection and fast tripping 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 predictive mitigation maturity and safety effectiveness. The regression model explained 74.6% of the variance in effectiveness, $R^2 = 0.746$, adjusted $R^2 = 0.736$, $F(6,145) = 70.94$, $p < 0.001$, with predictive mitigation maturity the leading predictor, $\beta = 0.32$, ahead of adaptive protection and fast tripping, $\beta = 0.26$, and predictive fault sensing and diagnostics, $\beta = 0.22$. The central finding is that arc-flash safety is decided less by any single device than by how tightly a plant couples sensing, prediction, interruption, and recovery into one fast loop — and that the plants protecting workers best are those that have matured that loop rather than assembled protective hardware piecemeal.*

***Keywords***
*Arc-flash mitigation; Predictive protection; Electrical safety; Manufacturing power systems; Incident energy.*

## INTRODUCTION

The most dangerous events in an industrial power system are also the fastest. When an arc fault strikes across energized conductors, it converts electrical energy into a flash of heat, blinding light, and a pressure wave in a matter of milliseconds, temperatures at the arc can exceed those on the surface of the sun, and a worker standing at the equipment may be burned before a conventional protective device has even finished deciding to open (Lee, 1982). This is the defining feature of the arc-flash hazard: its consequences are severe, and the window in which anything can be done about them is measured in cycles of the power waveform, not seconds. This study is about the systems manufacturers build to act within that window, predictive arc-flash mitigation, and about what makes those systems effective not only for safety but for the downtime and retrofit burdens that plant managers must weigh alongside it (Amir, 2025; Arif Uz et al., 2025; Zaman, 2024). The physics of the hazard is captured in the incident-energy model that underpins modern arc-flash analysis, given in Equation (1):

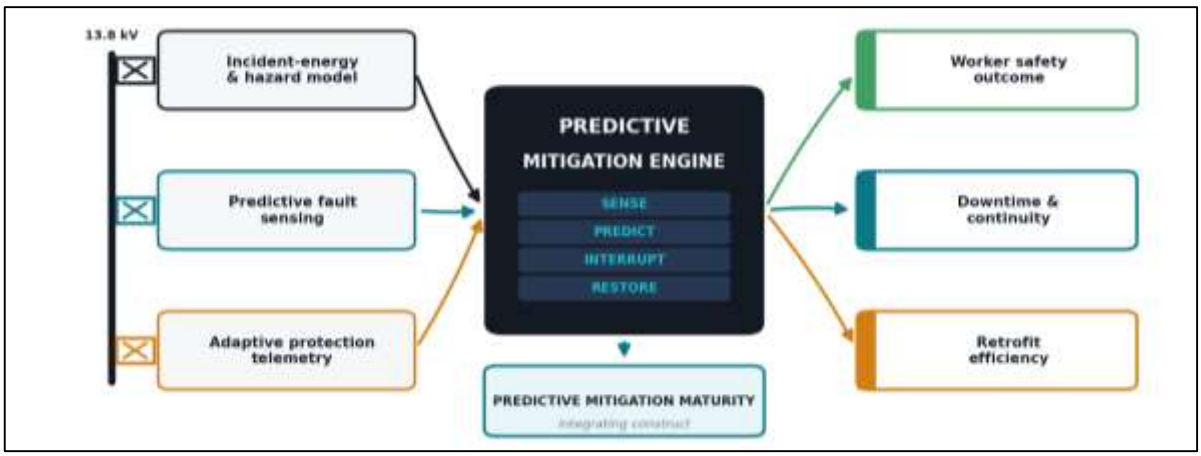
$$E = \frac{1}{2} C_f \, V \, I_{\text{arc}} \, t_{\text{arc}} \left( \frac{610^x}{D^x} \right), \qquad E \; [\text{cal/cm}^2] \quad (1)$$

Equation (1) expresses incident energy — the thermal energy a worker would receive at a given distance, in calories per square centimeter — as a function of arc current, arcing time, and working distance (Wilkins et al., 2004). One term in that equation is uniquely within an engineer's control: the arcing time. Incident energy scales directly with how long the arc burns, which is why the single most powerful lever in arc-flash mitigation is not more protective equipment but faster clearing of the fault (Doughty et al., 2000). The distance at which energy falls to a survivable threshold defines the arc-flash boundary, given in Equation (2):

$$D_B = \left[ \frac{C_f \, V \, I_{\text{arc}} \, t_{\text{arc}}}{E_B} \cdot 610^x \right]^{1/x} \quad (2)$$

Equation (2) inverts the energy relationship to find the boundary distance at which incident energy equals a chosen limit, the line beyond which unprotected workers are considered safe (Ammerman et al., 2010). Together these equations frame the study's central engineering insight: because energy grows with arcing time, a system that can predict and interrupt a fault faster shrinks the hazard at its source, reducing the protective equipment workers must wear and the boundary that must be cleared (IEEE, 2018).

**Figure 1: Predictive Arc-Flash Mitigation in U.S. Manufacturing Power Systems**




The study's central argument is that the effectiveness of arc-flash mitigation is decided less by any single protective device than by how tightly a plant couples sensing, prediction, interruption, and recovery into one fast, coherent capability. A fast relay is of little use if it cannot detect the fault promptly; an optical arc sensor that trips quickly but drops an entire production line unnecessarily trades one harm for another; a well-designed protection scheme that cannot be retrofitted into aging

switchgear without weeks of downtime may never be installed at all (Kumpulainen et al., 2014). Research on predictive maintenance and condition monitoring has repeatedly found that value comes from an integrated capability rather than from instruments in isolation (Jardine et al., 2006), and the same holds in arc-flash safety, where the cost of a fragmented system is counted in injuries that were preventable and in production stopped for protection that could have been faster and less disruptive (Mobley, 2002).

Three considerations make this an urgent subject for U.S. manufacturing specifically. First, much of the installed base is old: switchgear and motor control centers commissioned decades ago sit at the heart of plants, often with protection settings never optimized for arc-flash energy, so the hazard is both real and widespread (IEEE, 2007). Second, the regulatory and standards environment, workplace safety regulation together with consensus standards for electrical safety and incident-energy analysis — has made arc-flash assessment a legal and professional expectation rather than an option (NFPA, 2021), (OSHA, 2020). Third, the same sensing and analytics advances driving smart manufacturing now make genuinely predictive protection feasible, shifting the question from whether to sense and predict to how well the resulting capability performs (Lee et al., 2015). This study brings these threads together, framing hazard modeling, predictive sensing, adaptive protection, retrofit efficiency, and downtime impact as components of one capability whose contribution to worker safety can be estimated.

**Background of the Study**

Arc-flash safety began as a reactive discipline. For much of the twentieth century, protection against electrical faults focused on preventing equipment damage and clearing short circuits, with worker exposure to the arc itself treated as an unavoidable residual risk managed through distance and protective clothing (Lee, 1982). The recognition that the arc flash was a distinct, quantifiable, and mitigable hazard — rather than an incidental byproduct of a short circuit — reframed the problem, and led to the incident-energy models and boundary calculations that now anchor practice (Doughty et al., 2000). As these models matured, they revealed the leverage of arcing time and pushed attention toward faster protection (Wilkins et al., 2004).

The technical means of acting on that insight advanced in parallel. Fast bus-differential and zone-selective schemes reduced clearing times by coordinating relays more intelligently (Zimmerman & Costello, 2010); optical sensors that detect the light of an arc directly enabled tripping in as little as a couple of cycles, far faster than current-only schemes (Wilson et al., 2010); and arc-resistant equipment and remote-operation techniques reduced worker exposure during the highest-risk tasks (Parise et al., 2013). Meanwhile, the broader rise of condition monitoring and predictive maintenance offered a way to anticipate developing faults before they became arcs, using sensor data and analytics rather than fixed inspection intervals (Mobley, 2002). The convergence of these strands, faster protection and genuine prediction, is what makes predictive arc-flash mitigation, as distinct from reactive protection, a coherent capability worth studying (Hossan, 2025; Kanti, 2025). This background frames the study's motivation. The individual technologies, optical detection, fast protection, predictive analytics — are increasingly mature and available (Zhang et al., 2019). What remains uncertain is how manufacturers assemble them into a coherent capability, and how much that capability actually improves worker safety while controlling downtime and retrofit cost. The study addresses this by treating hazard modeling, predictive sensing, adaptive protection, retrofit efficiency, downtime impact, and overall mitigation maturity as measurable capabilities whose contributions can be estimated (DeLone & McLean, 2003).

**Problem Statement**

The problem this study addresses is that investment in arc-flash mitigation technology does not automatically translate into safer, more productive plants (Amir, 2026; Shima Ali et al., 2025). Manufacturers purchase fast relays, optical sensors, and updated protective equipment, yet workers continue to be exposed to severe incident energy because hazard models were never updated after equipment changed, because sensing did not cover the equipment where risk was highest, because protection was fast in theory but poorly coordinated in practice, or because a good scheme was never fully retrofitted into legacy switchgear (Kumpulainen et al., 2014). Where these weaknesses exist, mitigation spending produces compliance paperwork without producing safety. Plants that succeed, by contrast, appear to do so not by owning the most devices but by maturing an integrated capability,

which suggests that predictive mitigation maturity, the coherence with which sensing, protection, and recovery work together, may matter more than any single component (Teece, 2007). This matters because the stakes are measured in three currencies at once. An unmitigated arc flash can cause disabling burns or death, a human cost that dominates all others; but the mitigation itself carries operational costs, since aggressive protection can nuisance-trip and halt production, and retrofitting protection into live plants consumes scheduled downtime that manufacturers can ill afford (Ahuja & Khamba, 2008). A mitigation strategy that is safe but constantly interrupts production, or effective but impossible to retrofit affordably, fails a test that plant managers apply in practice (Mahmudul & Sadia, 2026; Shurovi, 2026). The study therefore investigates how a predictive arc-flash mitigation capability influences worker safety outcome effectiveness, and how its components shape the downtime and retrofit burdens that determine whether it is adopted at all.

**Objectives of the Study**

The general objective of this study was to assess how a predictive arc-flash mitigation capability, integrating hazard characterization, predictive sensing, adaptive protection, retrofit design, and downtime management, influences worker safety outcome effectiveness in U.S. manufacturing power systems. The specific objectives were: to examine the influence of arc-flash hazard characterization and incident-energy modeling on predictive mitigation maturity; to assess the relationship between predictive fault sensing and diagnostics and safety outcome effectiveness; to evaluate the effect of adaptive protection and fast tripping on effectiveness; to determine the role of retrofit design and integration efficiency in strengthening effectiveness; to test the effect of predictive mitigation maturity on effectiveness; and to examine the role of downtime and operational-continuity impact in shaping effectiveness. A further objective was to gauge mitigation maturity and capability gaps across the protection lifecycle.

**Research Hypotheses**

Six hypotheses guided the study. H1 held that arc-flash hazard characterization and incident-energy modeling significantly influence predictive mitigation maturity. H2 held that predictive fault sensing and diagnostics are significantly and positively related to worker safety outcome effectiveness. H3 held that adaptive protection and fast tripping significantly influence effectiveness. H4 held that retrofit design and integration efficiency significantly strengthen effectiveness. H5 held that predictive mitigation maturity significantly predicts effectiveness. H6 held that downtime and operational-continuity impact significantly shape effectiveness.

**Significance of the Research**

The study speaks to a decision that plant electrical and safety leaders face directly: where to invest so that arc-flash mitigation actually reduces harm without crippling production or blowing a retrofit budget. By separating the components of the capability and estimating their contributions, it indicates whether the priority should be better hazard modeling, broader predictive sensing, faster protection, more efficient retrofits, or the maturity that binds them (Mobley, 2002). Its framing of mitigation as a fast, closed protection loop is useful to power engineers, maintenance and reliability staff, and safety managers who must improve safety, uptime, and retrofit efficiency together, and its maturity index and capability priority matrix turn statistical findings into an improvement agenda. For scholarship, the study connects the power-protection, predictive-maintenance, and safety-science literatures around a single capability view, and provides evidence on which parts of a predictive-mitigation system most shape worker safety in manufacturing power systems (Reason, 1997).

## LITERATURE REVIEW

The literature relevant to predictive arc-flash mitigation sits at the intersection of fields that rarely cite one another: power-system protection in electrical engineering, incident-energy modeling in electrical safety, predictive maintenance in mechanical and reliability engineering, and safety science in human factors (Ali et al., 2026; Nurul, 2026). This review draws them together around one organizing claim — that arc-flash safety is a fast control loop, not a static barrier — and follows the path a fault travels: from the hazard that defines it, through the sensing that anticipates it and the protection that clears it, to the recovery and safety systems that surround it. The review is selective, tracing the thread most relevant to the study's argument.

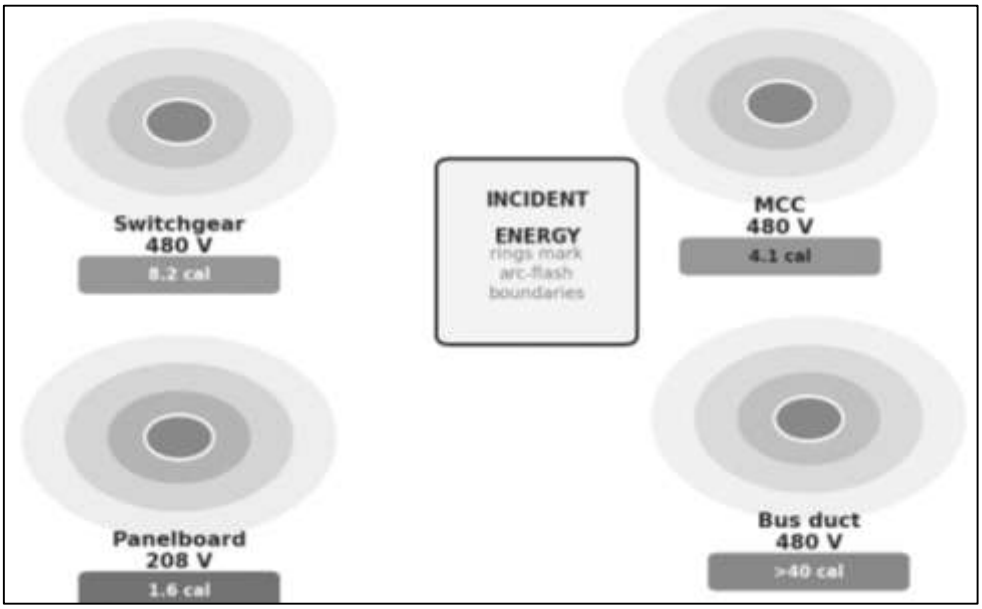
**The Arc-Flash Hazard and Incident-Energy Modeling**

The modern understanding of arc flash rests on the recognition that an electric arc is a distinct hazard with quantifiable thermal consequences, not merely a symptom of a short circuit (Lee, 1982). Foundational experimental work established relationships between arc characteristics and the energy delivered to a nearby worker, giving engineers a basis to predict burn injury (Doughty et al., 2000). This body of work matured into standardized calculation methods that estimate arcing current and incident energy from system parameters, the basis of the arc-flash studies now required in industrial facilities (IEEE, 2018). A key input to these methods is the arcing current, estimated from bolted-fault current and system voltage through empirical relationships, expressed in Equation (3):

$$\lg I_{\text{arc}} = K + 0.662 \lg I_{\text{bf}} + 0.0966\, V + 0.000526\, G + 0.5588\, V \lg I_{\text{bf}} \quad (3)$$

Equation (3) predicts arcing current from the available fault current, voltage, and electrode gap, a quantity that in turn drives both incident energy and the operating speed of protective devices (Wilkins et al., 2004). Complementary physical models of the arc itself have refined understanding of how arc energy develops in enclosures (Stokes & Sweeting, 2006), and comprehensive treatments have unified the calculation approaches used across the industry (Ammerman et al., 2010). The consistent lesson is that incident energy is not fixed by the hazard alone but depends heavily on how quickly protection acts, the insight the study builds upon.

**Figure 2: Arc-Flash Hazard across Manufacturing Equipment**




**Fast Protection and Adaptive Tripping**

Because incident energy grows with arcing time, reducing clearing time is the most direct engineering path to a smaller hazard, and the protection literature has pursued it along several lines. The total clearing time decomposes into detection, decision, and interruption intervals, as in Equation (4):

$$t_{\text{clear}} = t_{\text{detect}} + t_{\text{decide}} + t_{\text{interrupt}}, \qquad E \propto t_{\text{clear}} \quad (4)$$

Equation (4) makes explicit that incident energy is proportional to total clearing time, so shaving any of its components — detection, decision, or mechanical interruption — directly reduces the hazard (Zimmerman & Costello, 2010). Zone-selective interlocking and bus-differential schemes attack the decision interval by letting relays coordinate so that the device closest to a fault trips fastest without waiting for upstream time delays (Pasdar et al., 2013). Maintenance-mode settings that temporarily lower trip thresholds during high-risk work attack the same interval from another angle (Kumpulainen et al., 2014). The most dramatic reductions, however, come from attacking the detection interval directly, which is where optical sensing enters.

Optical arc-detection systems sense the intense light of an arc, often combined with a current check to avoid false trips, and can initiate tripping within a cycle or two, far faster than schemes that must wait to resolve current magnitude (Wilson et al., 2010). Their emergence turned fast protection from an exercise in relay coordination into one of direct arc sensing, and made genuinely sub-cycle detection feasible in industrial settings (Parise et al., 2013). The study treats adaptive protection and fast tripping as a core capability precisely because it acts on the one variable, arcing time, that most powerfully governs the hazard.

**Figure 3: Predictive Protection Signal Chain**

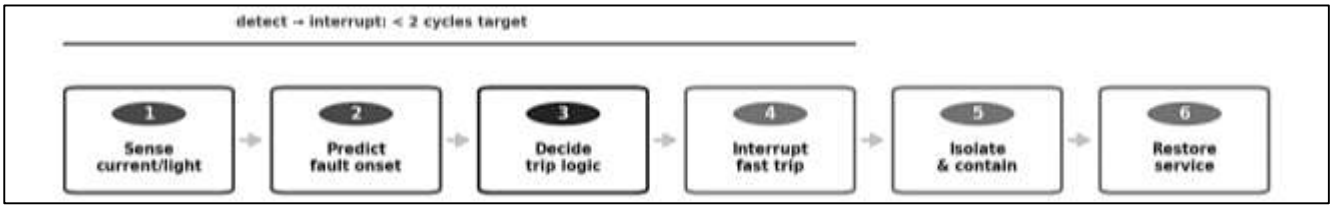
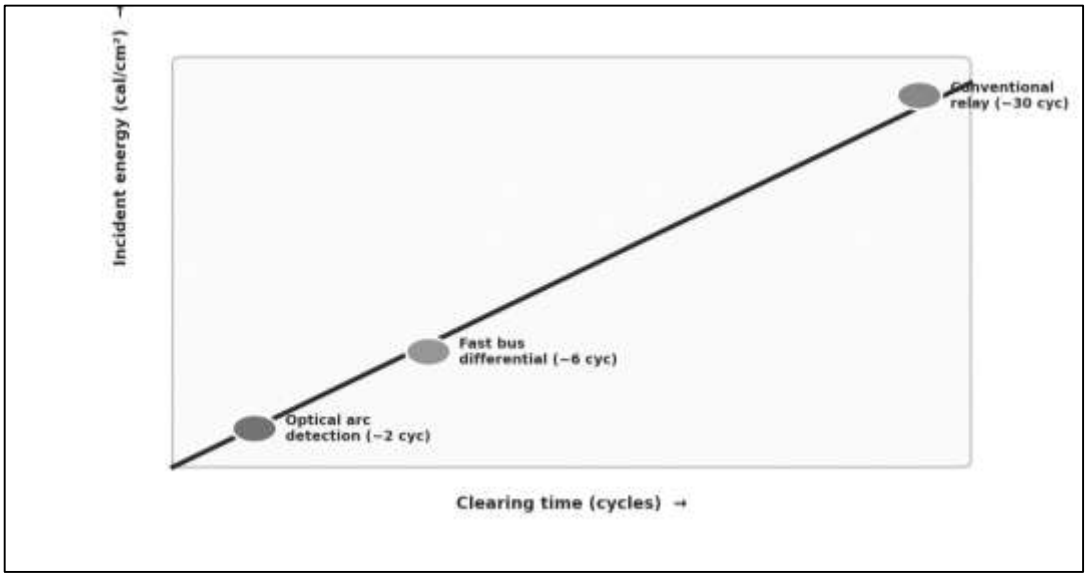



**Figure 4: Faster Clearing Cuts Incident Energy**




**Predictive Sensing, Diagnostics, and Prognostics**

Fast protection acts once a fault has begun; prediction aims to act before it does. This ambition comes from the predictive-maintenance tradition, which replaced fixed inspection intervals with condition-based intervention driven by sensor data (Mobley, 2002). The field's conceptual architecture — sensing, diagnosis of current condition, and prognosis of remaining useful life — provides the template for anticipating electrical faults before they arc (Jardine et al., 2006). Prognostics and health-management approaches extend this template further, coupling diagnosis of current condition with estimation of remaining useful life so that intervention can be timed before failure (Lee et al., 2014). Advances in machine learning have sharpened diagnosis and prognosis, enabling detection of incipient faults from subtle signatures in current, vibration, and thermal data (Lei et al., 2020). The machine-learning fault-diagnosis literature is now substantial, spanning classical feature-based methods and deep architectures that learn fault signatures directly from raw signals (Liu et al., 2018), (Hoang & Kang, 2019). Cyber-physical and industrial-IoT frameworks provide the sensing and data infrastructure to apply these methods at plant scale (Gungor et al., 2010), and predictive-maintenance systems built on them have demonstrated measurable reductions in unplanned failures (Susto et al., 2015). Evaluating such predictors requires care, because faults are rare and the cost of false alarms is high; standard detection measures capture the balance, as in Equation (5):

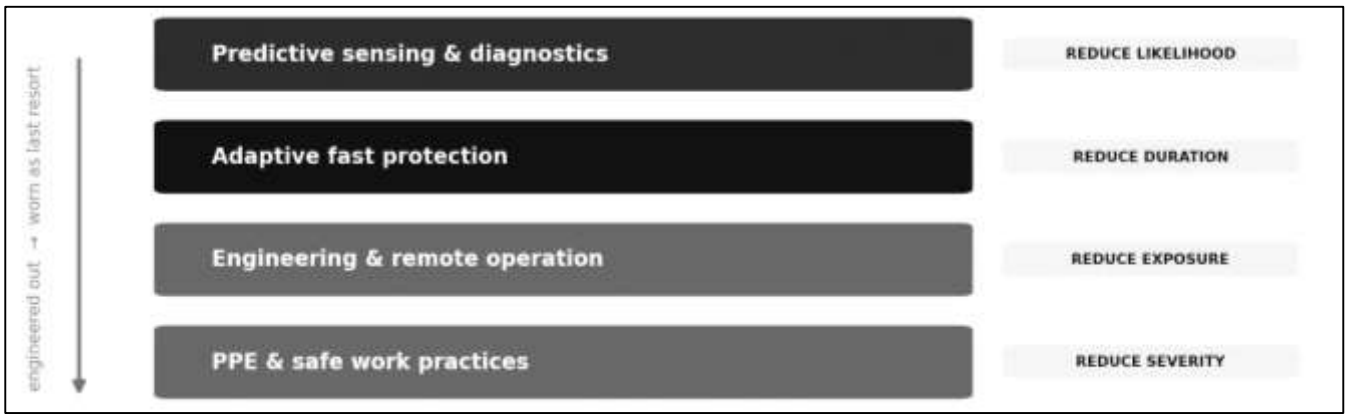
$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad F_1 = \frac{2\,\mathrm{P} \cdot \mathrm{R}}{\mathrm{P} + \mathrm{R}} \qquad (5)$$

The precision, recall, and F-measures in Equation (5) quantify how well a predictor distinguishes genuine incipient faults from normal variation (Davis & Goadrich, 2006). Under the severe class imbalance typical of rare faults, these measures are more informative than raw accuracy, and the balance they express matters operationally, since a predictor that cries wolf will be silenced and one that misses faults offers no protection (Powers, 2011). The study treats predictive fault sensing and diagnostics as the capability that shifts mitigation from reactive to anticipatory.

**Reliability, Downtime, and Operational Continuity**

Any intervention in a plant's protection scheme touches production, which is why downtime is inseparable from safety in the manufacturing context. Reliability engineering provides the tools to reason about this trade-off, modeling the availability of power systems and the consequences of interruption (Billinton & Allan, 1992), and industry-specific methods quantify the reliability of industrial and commercial power systems in particular (IEEE, 2007). The manufacturing operations literature adds the discipline of total productive maintenance, which frames unplanned downtime as a loss to be systematically eliminated (Nakajima, 1988), and empirical studies link maintenance practices to operational performance (Ahuja & Khamba, 2008). For arc-flash mitigation, the implication is twofold: protection that nuisance-trips imposes downtime, while predictive approaches that catch faults early can avert the far larger downtime of a destructive failure. The study captures this tension in its downtime and operational-continuity construct.

**Figure 5: Layered Arc-Flash Mitigation Strategy**




**Retrofit, Smart Manufacturing, and Digital Approaches**

Most arc-flash mitigation in the United States happens not in new construction but as retrofits into existing plants, which makes the efficiency of retrofitting a first-order concern (Amir & Chapal, 2022; Abdur & Iftekhar, 2021). Capital-project and earned-value research provides methods for planning and controlling such projects, where schedule and downtime are tightly constrained (Cooke, 2003), (Fleming & Koppelman, 2016), and cost-benefit analysis offers a framework for weighing mitigation investment against risk reduction (Boardman et al., 2018). At the same time, the smart-manufacturing and Industry 4.0 movements are reshaping what is possible, embedding sensing and analytics throughout the plant (Lee et al., 2015), (Kang et al., 2016). Digital-twin approaches, which maintain a live model of physical equipment, offer a route to simulating arc-flash scenarios and tuning protection without interrupting production (Tao et al., 2018), (Qi & Tao, 2018).

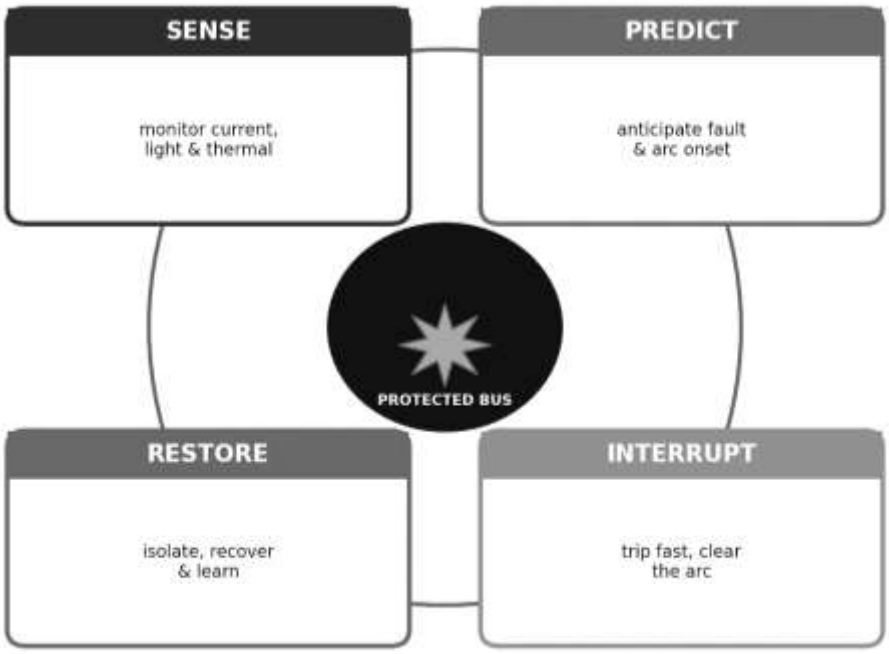
**The Sense–Predict–Interrupt–Restore (SPIR) Protection Loop**

The capabilities reviewed above are usually studied apart, but in an effective mitigation program they operate as a single fast loop, and describing that loop is the study's central theoretical contribution (Hasan & Uddin, 2022; Mohiul & Badrul, 2022; Kanti & Rony, 2022). It proposes the Sense–Predict–Interrupt–Restore (SPIR) protection loop: a continuous hazard-control cycle through which a manufacturing power system anticipates and clears arc-flash faults. In the sense phase, current, light, thermal, and condition data are continuously monitored (Golam & Amir, 2023; Tohidul, 2023; Sadia et al., 2022). In the predict phase, diagnostics and prognostics anticipate developing faults and imminent arcs. In the interrupt phase, adaptive protection trips fast to clear the arc and minimize incident energy

(Badrul & Mominul, 2023; Hossan & Adar, 2023; Risha & Khalid, 2023). In the restore phase, the system isolates the fault, recovers service, and learns from the event, feeding incidents and near-misses back to refine models and protection settings, closing the loop (Amir, 2024; Hossan, 2024; Shima Ali et al., 2024).

The SPIR loop rests on three theoretical foundations. From defense-in-depth safety theory it takes its layered logic: safety in hazardous systems comes from multiple independent barriers, reducing likelihood, duration, exposure, and severity, so that no single failure is catastrophic (Reason, 1997). This layered logic has deep roots in industrial safety, where early accident-prevention theory established that serious injuries sit atop a much larger base of minor incidents and near-misses, so that attending to the many precursors is the route to preventing the rare catastrophe (Heinrich et al., 1980). From condition-based maintenance and resilience engineering it takes the premise that safety is an active, ongoing capacity to anticipate and respond to developing threats, not a static state certified once (Hollnagel et al., 2006). And from socio-technical systems theory it takes the insight that the automated protective technology and the human maintenance and safety practices around it must be designed together, since fast protection without the discipline to maintain it, or predictive analytics without the organization to act on them, leaves the loop broken (Trist, 1981). The integrating construct in the framework, predictive mitigation maturity, measures how tightly the loop is closed — how smoothly sensing flows into prediction, interruption, and recovery (Rasmussen, 1997).

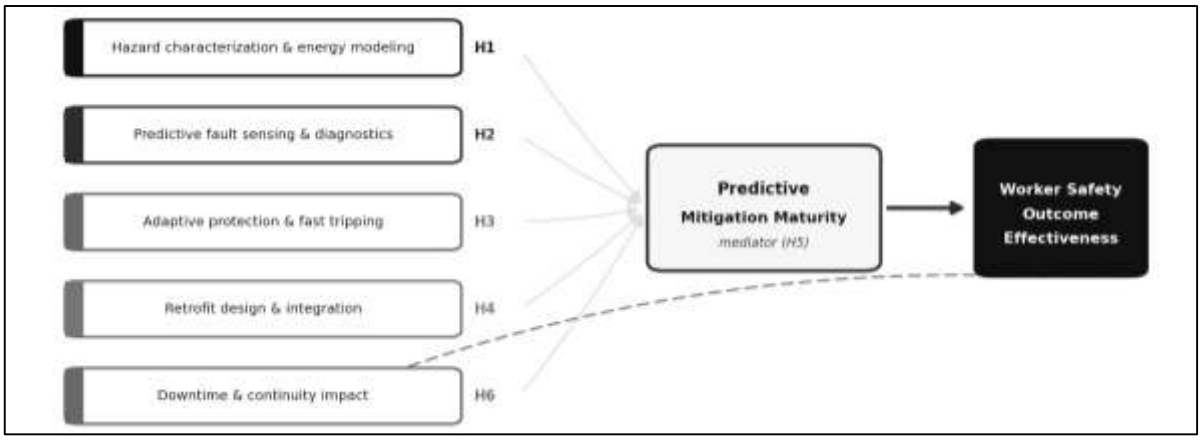
**Figure 6: The Sense–Predict–Interrupt–Restore (SPIR) Protection Loop**




**Conceptual Framework**

Rendering the SPIR loop as a testable model, the study positions six capabilities as drivers of worker safety outcome effectiveness, with predictive mitigation maturity acting as the integrating construct through which the others largely operate. Arc-flash hazard characterization, predictive fault sensing, adaptive protection and fast tripping, retrofit design and integration, and downtime and continuity impact each contribute to effectiveness, while predictive mitigation maturity captures the coherence with which they are combined and is expected to be the strongest single predictor (Teece, 2007). The conceptual model, shown in Figure 7, includes a feedback path from realized safety outcomes back to the hazard-modeling and sensing capabilities, reflecting the closed-loop logic of the protection cycle and distinguishing it from linear views in which protection simply trips and stops (Hollnagel et al., 2006).

**Figure 7: Conceptual Model for Worker Safety Outcome Effectiveness**




## METHODS

### Research Design

The study used a quantitative, cross-sectional, case-based design, suited to measuring perceptions of a predictive arc-flash mitigation capability across a defined population at one point in time and to testing hypothesized relationships among latent constructs (Venkatesh et al., 2003). A survey strategy was appropriate because the constructs — hazard characterization, predictive sensing, adaptive protection, retrofit efficiency, downtime impact, mitigation maturity, and safety outcome effectiveness — are best judged by the engineers and safety professionals who design, install, and operate these systems and can assess how well they function in practice. The design favors comparability across respondents over the depth of a single plant, allowing the relative contribution of each capability to be estimated.

### Population and Sampling

The target population comprised professionals engaged in electrical protection and arc-flash safety in U.S. manufacturing power systems. A purposive sampling strategy reached respondents with direct, informed exposure to the constructs, appropriate when the aim is expert assessment rather than broad generalization (Venkatesh et al., 2003). Of 170 questionnaires distributed, 161 were returned and 152 were retained after screening for completeness and engagement, a valid response rate of 89.4%. The sample spanned electrical and power engineers, plant maintenance and reliability staff, EHS and safety managers, protection and controls specialists, and facilities and operations managers, with 69.1% reporting direct involvement in power-system protection or plant electrical safety.

**Table 1: Response Rate Summary**

| Category | Count | Percentage |
|---|---|---|
| Distributed | 170 | 100.0% |
| Returned | 161 | 94.7% |
| Valid and used | 152 | 89.4% |
| Excluded after screening | 9 | 5.3% |

**Table 2: Respondent Demographics (n = 152)**

| Characteristic | Category | n | % |
|---|---|---|---|
| Role | Electrical / power engineers | 38 | 25.0% |
| | Plant maintenance & reliability | 34 | 22.4% |
| | EHS / safety managers | 30 | 19.7% |
| | Protection & controls specialists | 27 | 17.8% |
| | Facilities / operations mgmt | 23 | 15.1% |
| Experience | 1–5 years | 26 | 17.1% |
| | 6–15 years | 63 | 41.4% |
| | More than 15 years | 63 | 41.4% |

**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 power-system protection, predictive maintenance, safety management, and information-systems success research, then refined for the arc-flash mitigation context (DeLone & McLean, 2003). The seven constructs were arc-flash hazard characterization and incident-energy modeling, predictive fault sensing and diagnostics, adaptive protection and fast tripping, retrofit design and integration efficiency, downtime and operational-continuity impact, predictive mitigation maturity, and worker safety outcome effectiveness. 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 safety outcome effectiveness. A maturity index and a capability priority matrix then translated the statistics into practical terms. Reliability was quantified with coefficient alpha, given in Equation (6):

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_i^2}{\sigma_T^2}\right) \tag{6}$$

In Equation (6), 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 integrating construct, predictive mitigation maturity, was constructed as a weighted mean of its component capabilities, as in Equation (7):

$$\mathrm{PMM} = \sum_{c=1}^{C} w_c \bar{x}_c, \qquad \sum_{c=1}^{C} w_c = 1, \quad w_c \geq 0 \tag{7}$$

Equation (7) aggregates the constituent capability scores into a single maturity measure, with weights summing to one. The central test of the study's model used multiple regression, specified in Equation (8):

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

Equation (8) regresses worker safety outcome effectiveness 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.

**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 capabilities as strong, with meaningful variation. Worker safety outcome effectiveness recorded the highest mean at 4.28, and arc-flash hazard characterization and incident-energy modeling the lowest at 3.92, a pattern consistent with the study's argument that the foundational work of accurately modeling the hazard is often the least complete even where outcomes are valued (IEEE, 2018).

**Table 3: Descriptive Statistics of Study Variables**

| Variable | Mean | SD |
|---|---|---|
| Worker safety outcome effectiveness | 4.28 | 0.51 |
| Adaptive protection & fast tripping | 4.20 | 0.54 |
| Predictive mitigation maturity | 4.13 | 0.55 |
| Predictive fault sensing & diagnostics | 4.08 | 0.58 |
| Downtime & operational continuity | 4.03 | 0.61 |
| Retrofit design & integration | 3.97 | 0.63 |
| Hazard characterization & energy modeling | 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 effectiveness 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 |
|---|---|---|---|
| Worker safety outcome effectiveness | 6 | 0.94 | Reliable |
| Predictive mitigation maturity | 6 | 0.92 | Reliable |
| Adaptive protection & fast tripping | 5 | 0.90 | Reliable |
| Predictive fault sensing & diagnostics | 6 | 0.88 | Reliable |
| Downtime & operational continuity | 5 | 0.86 | Reliable |
| Retrofit design & integration | 5 | 0.85 | Reliable |
| Hazard characterization & energy modeling | 6 | 0.83 | Reliable |

**Correlation Analysis**

Table 5 reports Pearson correlations among the constructs. All were positive and statistically significant, consistent with an integrated system in which the capabilities move together (Jardine et al., 2006). The strongest association was between predictive mitigation maturity and worker safety outcome effectiveness, $r = 0.80$, followed by the correlation between adaptive protection and effectiveness, $r = 0.73$. 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 | Hazard | Sensing | Protect | Retrofit | Downtime | Matur. | Safety |
|---|---|---|---|---|---|---|---|
| Hazard characterization | 1.00 | | | | | | |
| Predictive sensing | 0.60 | 1.00 | | | | | |
| Adaptive protection | 0.58 | 0.64 | 1.00 | | | | |
| Retrofit integration | 0.55 | 0.58 | 0.60 | 1.00 | | | |
| Downtime & continuity | 0.56 | 0.59 | 0.61 | 0.57 | 1.00 | | |
| Mitigation maturity | 0.70 | 0.69 | 0.70 | 0.65 | 0.66 | 1.00 | |
| Safety effectiveness | 0.64 | 0.71 | 0.73 | 0.67 | 0.69 | 0.80 | 1.00 |

**Regression Analysis**

Table 6 reports the regression model summary and Table 7 the coefficients. The six capabilities jointly explained 74.6% of the variance in worker safety outcome effectiveness, $R^2 = 0.746$, adjusted $R^2 = 0.736$, and the model was highly significant, $F(6,145) = 70.94$, $p < 0.001$ (Boardman et al., 2018).

**Table 6: Regression Model Summary**

| Statistic | Value |
|---|---|
| R | 0.864 |
| $R^2$ | 0.746 |
| Adjusted $R^2$ | 0.736 |
| Std. error of estimate | 0.268 |
| F (6, 145) | 70.94 |
| Significance (p) | < 0.001 |

Predictive mitigation maturity was the strongest predictor, β = 0.32, followed by adaptive protection and fast tripping, β = 0.26, and predictive fault sensing and diagnostics, β = 0.22; retrofit design, hazard characterization, and downtime impact were significant but smaller contributors. The dominance of maturity supports the study's core claim that closing the protection loop, more than any single component, drives safety.

**Table 7: Regression Coefficients**

| Predictor | β | t | p |
|---|---|---|---|
| Predictive mitigation maturity | 0.32 | 4.88 | < 0.001 |
| Adaptive protection & fast tripping | 0.26 | 3.99 | < 0.001 |
| Predictive fault sensing & diagnostics | 0.22 | 3.40 | 0.001 |
| Downtime & operational continuity | 0.19 | 2.96 | 0.004 |
| Hazard characterization & energy modeling | 0.16 | 2.61 | 0.010 |
| Retrofit design & integration | 0.14 | 2.29 | 0.023 |

## 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 predictive mitigation maturity's effect on effectiveness was both significant and the largest in the model, consistent with its theorized role as the integrating construct that closes the protection loop (Teece, 2007).

**Table 8: Summary of Hypothesis Testing**

| Hypothesis | Path | β / r | Result |
|---|---|---|---|
| H1 | Hazard characterization → mitigation maturity | r = 0.70 | Supported |
| H2 | Predictive sensing → safety effectiveness | β = 0.22 | Supported |
| H3 | Adaptive protection → safety effectiveness | β = 0.26 | Supported |
| H4 | Retrofit integration → safety effectiveness | β = 0.14 | Supported |
| H5 | Mitigation maturity → safety effectiveness | β = 0.32 | Supported |
| H6 | Downtime & continuity → safety effectiveness | β = 0.19 | Supported |

## PREDICTIVE MITIGATION MATURITY ANALYSIS

To turn the constructs into a practical diagnostic, the study computed a maturity index across the stages of the protection lifecycle. 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 lifecycle stages, while the gap for each capability area is the difference between its rated importance and its rated effectiveness (Hollnagel et al., 2006). Table 9 reports maturity by stage. The overall index was 4.06, indicating generally mature capabilities, with hazard modeling and protection tuning relatively strong and retrofit integration and continuous review comparatively weaker — a profile consistent with plants that have invested in analysis and protective hardware faster than in the retrofit execution and ongoing review that keep a scheme current (IEEE, 2007).

**Table 9: Predictive Mitigation Maturity by Lifecycle Stage**

| Lifecycle Stage | Maturity (1–5) | Level |
|---|---|---|
| Hazard modeling | 4.14 | High |
| Protection tuning | 4.13 | High |
| Predictive sensing | 4.12 | High |
| Safety governance | 4.08 | High |
| Downtime management | 4.05 | High |
| Retrofit integration | 4.01 | High |
| Continuous review | 3.99 | Moderate–High |

## ARC-FLASH MITIGATION 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 improvement agenda (Mobley, 2002). Table 10 reports the results, ordered by gap. The largest gaps appeared in real-time arc-fault prediction, fast-tripping response time, and incident-energy model accuracy, indicating that respondents most wanted their systems to anticipate faults in real time, to clear them faster, and to model the hazard more accurately. These priorities map cleanly onto the SPIR loop: they concentrate in the sense, predict, and interrupt phases, where the raw capacity to anticipate and clear a fault is formed (Wilson et al., 2010).

**Table 10: Arc-Flash Mitigation Capability Priority Matrix**

| Capability Area | Importance | Effectiveness | Gap | Priority |
|---|---|---|---|---|
| Real-time arc-fault prediction | 4.75 | 3.66 | 1.09 | Very High |
| Fast-tripping response time | 4.70 | 3.62 | 1.08 | Very High |
| Incident-energy model accuracy | 4.62 | 3.58 | 1.04 | Very High |
| Protection coordination | 4.55 | 3.66 | 0.89 | High |
| Retrofit-downtime minimization | 4.58 | 3.55 | 1.03 | High |
| Sensor coverage & placement | 4.60 | 3.70 | 0.90 | High |
| Maintenance data integration | 4.42 | 3.80 | 0.62 | Moderate |
| PPE compliance & training | 4.40 | 3.78 | 0.62 | Moderate |

## FINDINGS

Assembled, the results tell a consistent story. First, respondents regard their predictive-mitigation capabilities as broadly strong: every construct sat in the high band, with safety effectiveness and adaptive protection 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 fast loop rather than independent devices (Jardine et al., 2006). Third, and most importantly, the capabilities jointly explain a large share of the variance in safety outcome effectiveness, 74.6%, and predictive mitigation maturity is the strongest single predictor, ahead of adaptive protection and predictive sensing. Fourth, the maturity and priority analyses locate where the capabilities are strongest and weakest. Maturity is highest in hazard modeling and protection tuning and lowest in retrofit integration and continuous review, while the widest capability gaps lie in real-time arc-fault prediction, fast-tripping response time, and incident-energy model accuracy. The consistent implication is that the frontier of improvement is not more protective hardware in isolation but faster, more accurate anticipation and clearing of faults, built on models that reflect the real installed system (Kumpulainen et al., 2014). This is exactly what the SPIR framework predicts: safety rises when the sense, predict, interrupt, and restore phases reinforce one another, and the greatest returns come from strengthening the phases that govern how quickly and accurately a developing fault is caught and cleared. The downtime and retrofit findings reinforce this reading: because faster, predictive clearing averts destructive failures and because efficient retrofits determine whether good protection is ever installed, the same maturity that drives safety also protects production and eases the retrofit burden — the three outcomes move together rather than in tension (Ahuja & Khamba, 2008).

## DISCUSSION

The results support the study's central proposition: that arc-flash safety is decided less by any single protective device than by how tightly a plant couples sensing, prediction, interruption, and recovery into one fast loop. The dominance of predictive mitigation maturity as a predictor, $\beta = 0.32$, is the clearest expression of this. Read through the Sense–Predict–Interrupt–Restore loop, maturity measures how smoothly sensing flows into prediction, interruption, and recovery, so its strength as a predictor reflects the framework's premise that safety emerges from the coherence of the whole cycle rather than from any single phase (Teece, 2007).

The strong effect of adaptive protection and fast tripping, $\beta = 0.26$, the second-largest, confirms the engineering insight at the heart of arc-flash mitigation: because incident energy scales with arcing time, the speed of clearing is the single most powerful lever on the hazard (Doughty et al., 2000). This is consistent with the protection literature's emphasis on reducing clearing time through zone-selective

schemes and optical detection (Zimmerman & Costello, 2010). Notably, respondents rated protection highly yet flagged fast-tripping response time and real-time arc-fault prediction as among their largest capability gaps, which suggests that the frontier is not protection in the abstract but protection fast and anticipatory enough to shrink the hazard before a worker is exposed (Wilson et al., 2010). This echoes a recurring theme: the value of speed compounds when it is coupled to prediction, so that faults are caught as they develop rather than only as they arc.

The significant effect of predictive fault sensing and diagnostics, $\beta = 0.22$, together with the foundational role of hazard characterization — its strong correlation with maturity, $r = 0.70$, and significant regression effect, $\beta = 0.16$ — confirms that fast protection must rest on accurate anticipation and modeling. That hazard characterization recorded the lowest mean of any construct, 3.92, while remaining a significant driver and carrying one of the largest capability gaps, mirrors a persistent theme in electrical-safety practice: incident-energy studies are often performed once and left to age as the plant changes, so the model that protection relies on drifts away from the system it describes (IEEE, 2018). Plants appear to recognize accurate hazard modeling as both essential and incomplete, which is precisely the profile of a foundational capability warranting renewed investment (Ammerman et al., 2010).

The significant contributions of downtime and operational continuity, $\beta = 0.19$, and retrofit design and integration, $\beta = 0.14$, though smaller, reinforce the practical logic of the framework. Downtime matters because protection that nuisance-trips or that averts destructive failure directly shapes production, tying safety to continuity (Ahuja & Khamba, 2008); retrofit efficiency matters because most mitigation in U.S. plants is retrofitted into aging systems, and a scheme that cannot be installed affordably is never installed at all (Cooke, 2003). The comparatively lower maturity of retrofit integration and continuous review, and the persistence of gaps there, indicate that the execution and upkeep side of mitigation lags the analysis and hardware side — precisely the imbalance the SPIR framework warns against, since a protection loop that is designed but not maintained, or specified but not fully retrofitted, leaves the plant exposed (Hollnagel et al., 2006). Taken together, the findings describe capabilities that are strong at modeling and protecting but comparatively weaker at anticipating in real time and at executing efficient, well-maintained retrofits, and they locate the greatest returns to improvement in closing those gaps rather than in acquiring more hardware (Mobley, 2002). Crucially, the three outcomes the study set out to weigh — safety, downtime, and retrofit efficiency — emerge as complements rather than competitors: the maturity that clears faults fastest also averts the destructive failures that cause the longest downtime, and disciplined retrofit practice is what puts that maturity in place (Billinton & Allan, 1992).

## CONCLUSION

This study set out to assess how a predictive arc-flash mitigation capability, understood as an integrated system, influences worker safety outcome effectiveness in U.S. manufacturing power systems, and how it shapes the downtime and retrofit burdens that determine adoption. Using a quantitative, cross-sectional design and responses from 152 electrical and safety professionals, it found that all six hypothesized relationships held and that the capabilities together explained 74.6% of the variance in safety effectiveness. Predictive mitigation maturity emerged as the strongest predictor, underscoring that the coherence with which sensing, protection, and recovery are coupled matters more than any single element. Adaptive protection and predictive sensing followed, while retrofit design, hazard characterization, and downtime impact were significant but smaller contributors.

The study concludes that arc-flash mitigation is best understood not as a device that trips when a fault occurs but as a fast control loop that anticipates, clears, and recovers from faults and learns from each event. The Sense–Predict–Interrupt–Restore cycle offers a way to see that loop whole: conditions are sensed, developing faults predicted, arcs interrupted quickly, and service restored, with incidents feeding back to refine models and settings. Safety rises when these phases reinforce one another, and the evidence here indicates that the phases most in need of strengthening are the real-time anticipation of faults and their fast, accurate clearing. Importantly, the study finds that safety, uptime, and retrofit efficiency move together rather than in tension: the maturity that protects workers also protects production and, through disciplined retrofit practice, becomes affordable to install. For plants, the practical message is to invest in closing the loop — in accurate hazard models, real-time predictive

sensing, fast adaptive protection, and efficient retrofits — rather than in isolated devices; for scholarship, the study shows the value of joining the power-protection, predictive-maintenance, and safety-science literatures around a single capability view of electrical safety.

## RECOMMENDATIONS

Several recommendations follow from the findings. First, plants should treat arc-flash hazard characterization and incident-energy modeling as a living, first-order investment, updating studies as equipment and settings change rather than filing them once, since hazard modeling was both the lowest-rated capability and a significant driver of effectiveness, and its accuracy caps everything protection relies on. Second, they should prioritize real-time predictive sensing and fast tripping, which respondents identified as their most important capability gaps, so that faults are anticipated and cleared before workers are exposed.

Third, plants should invest in optical and multi-signal arc detection coupled with zone-selective and maintenance-mode protection, attacking the detection and decision intervals that most directly govern incident energy. Fourth, they should plan retrofits for efficiency, using capital-project and downtime-minimization discipline so that good protection schemes are actually installed rather than deferred for lack of an affordable outage window. Fifth, they should manage downtime and safety together, recognizing that predictive clearing which averts destructive failures protects production as well as workers. Finally, plants should manage arc-flash mitigation as an integrated capability, using a maturity assessment and a capability priority matrix to direct improvement toward the weakest phases of the Sense–Predict–Interrupt–Restore loop rather than toward isolated devices, and pursuing digital-twin simulation and continuous review as the path to keeping the loop current.

## LIMITATIONS OF THE STUDY

This study has several limitations. First, the cross-sectional design captured perceptions at a single point in time and cannot establish causal direction or track how capabilities and safety outcomes co-evolve; a longitudinal design would allow stronger causal inference and better capture the closed-loop dynamics central to the SPIR framework. Second, the study relied on perceptual, self-reported measures completed by professionals, so the results reflect informed assessment rather than objective measurement of incident energy, clearing time, or injury rates; future work could pair perception data with hard metrics such as measured clearing times, calculated incident energy, recordable injury rates, and downtime hours. Third, the purposive sample, while appropriate for reaching knowledgeable respondents, limits generalizability to the broader population of manufacturing facilities, which vary widely in age, sector, and electrical infrastructure. Fourth, the constructs were assessed at a general level, and the relative importance of specific capabilities may differ across industries, plant ages, and voltage classes. Finally, the study did not directly measure the capital cost or return on investment of mitigation upgrades, which is a decisive practical consideration and a promising avenue for future research.

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