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Quantifying Learning Dynamics in Saudi Fintech Software Reliability: An Enhanced NHPP-SW Model for SAMA-Compliant Systems

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Abstract. A In alignment with Saudi Arabia’s Vision 2030 and the Saudi Central Bank (SAMA) regulatory directives, the financial sector is undergoing rapid digital transformation, increasing the demand for reliable fintech software systems. This study introduces an Enhanced Schick-Wolverton Non-Homogeneous Poisson Process (NHPP-SW) model that integrates a learning parameter (α) to reflect organizational learning, coordination efficiency, and regulatory adaptation. Calibrated using simulated defect-arrival data representative of ten prominent Saudi fintech firms, the model parameters were estimated through nonlinear least-squares optimization via the Levenberg-Marquardt algorithm. Evaluation against standard reliability metrics including Root Mean Square Error (RMSE), Mean Square Error (MSE), and the Mean Value Function (MVF) demonstrates the model’s high predictive accuracy, with relative RMSE consistently below 5%. Beyond technical performance, the model offers practical value for financial institutions by enabling early detection of readiness for regulatory compliance, optimizing resource allocation for testing and quality assurance, and providing objective benchmarks for reliability growth. The results affirm the model’s utility as a strategic decision-support tool for enhancing software reliability and ensuring regulatory alignment within the evolving Saudi fintech landscape.

Keywords: NHPP, software reliability growth modeling, learning curve dynamics, fintech reliability, SAMA compliance, Vision 2030, Saudi Arabia, parameter estimation

1. Introduction

The Kingdom's fintech ecosystem has expanded dramatically, growing from fewer than 20 startups in 2018 to 216 SAMA-permitted firms in 2023, surpassing the initial Vision 2030 target by 44 percent (Fintech Saudi, 2023). The *2024 Financial Stability Report* confirms that Saudi Arabia's payment volumes and resilience indicators continued to strengthen through 2024 despite global headwinds (Saudi Central Bank [SAMA], 2024). Today, SAMA's tiered Regulatory Sandbox and continually updated Cyber Security Framework make operational reliability a licensing demand, not just a competitive advantage (SAMA, 2025; Saudi Information Security Association [SISA], 2024). Studies have established a correlation between corporate governance and FinTech decisions in the Saudi banking sector. An analysis of data from 12 Saudi banks between 2014 and 2019 found that larger board sizes negatively correlate with FinTech service quality, suggesting that bigger boards may hinder technological innovation. Conversely, more independent and effective governance structures appear to facilitate the adoption of high-quality and reliable FinTech solutions, particularly those supporting regulatory compliance. These findings highlight how governance dynamics can directly influence not only innovation capacity but also the reliability of systems used for regulatory oversight and risk management (Al-Mubarak & Aljughaiman, 2024). The growing reliance on FinTech in banking has raised concerns about the reliability of systems for regulatory compliance. Reliable software is essential for ensuring digital platforms meet financial regulations. Non-Homogeneous Poisson Process (NHPP) models are increasingly used to assess software reliability over time, offering a framework for modeling fault detection. Recent studies have explored how corporate governance affects FinTech adoption in Saudi banks, aiming to enhance the quality and reliability of these systems. Traditional NHPP models, designed for static fault detection rates, struggle to address the rapid learning cycles and process improvements inherent in agile fintech teams. A meta-analysis has identified over 250 extensions of NHPP (Chen & Ma, 2025; Khalid, Ahmed, & Raza, 2024), underscoring the model's limitations. These classical approaches assume constant fault rates and fail to reflect the dynamic environments of modern software development. The foundations of software reliability modeling were established by the Jelinski-Moranda (JM) model in 1972, which was based on the probability of remaining faults (Jelinski & Moranda, 1972). This model was later refined into the Schick-Wolverton (SW) model in 1978, which assumes that the failure rate increases between successive faults. This assumption makes the SW model more suitable for real-world testing environments, where both the number of remaining faults and the time allocated for debugging influence failure behavior (Schick & Wolverton, 1978). Later extended to incorporate NHPPs that describe failure behavior over time through a mean value function (MVF) and a failure intensity rate (Goel & Okumoto, 1979). Over time, researchers have refined these models to reflect more realistic conditions. Some models introduced organizational learning effects to represent improved fault detection as testing progresses (Aggarwal et al., 2024; Lee et al., 2023). Others addressed imperfect debugging, where faults may be reintroduced during correction (Samal, 2024), or considered uncertainty in operating environments (Wang et al., 2023). Additional extensions have modeled interacting or heterogeneous fault types through multivariate NHPPs (Song et al., 2024; Chang et al., 2017), while others differentiated between transient and permanent faults (Kim et al., 2019), or proposed unified frameworks to accommodate various fault detection patterns (Li et al., 2024). Collectively, these enhancements have improved the realism and adaptability of NHPP-based software reliability growth models. The NHPP framework has been progressively refined to address limitations encountered in real-world software testing scenarios. For example, S-shaped growth models were introduced to reflect delayed learning effects commonly observed in practical environments (Yamada, Ohba, & Osaki, 1983). To account for the non-ideal nature of debugging, imperfect correction models were proposed, allowing for the possibility of introducing new faults during the fault-removal process (Pham & Zhang, 1997). The concept of learning curves within the field of software engineering has been the subject of extensive research, particularly regarding team productivity and the efficiency of defect detection. Nevertheless, the integration of learning dynamics into reliability growth models remains an area with limited exploration. This study seeks to address this gap by incorporating learning parameters that reflect organizational maturity, coordination overhead, and regulatory adaptation capabilities. Recent complementary advancements include the application of deep learning ensembles for residual defect prediction (Huang, Zhao, & Lin, 2024) as well as hybrid models that combine NHPP with machine learning techniques, which are capable of adaptive responses to evolving development conditions (Park, Min, & Lee, 2023).

The intersection of software reliability and regulatory compliance represents a critical research frontier. Feyen, Frost, Gambacorta, and Natarajan (2021) provide a comprehensive analysis of fintech's digital transformation impact on financial services, emphasizing the critical role of robust software systems in maintaining regulatory compliance. Pham, Le, and Tran (2024) specifically examine the relationship between fintech development and banking performance, highlighting the importance of reliable software systems in maintaining competitive advantage. The Saudi fintech ecosystem presents unique challenges due to the rapid pace of regulatory evolution and the diverse organizational maturity levels of market participants. SAMA's regulatory sandbox approach requires adaptive reliability assessment frameworks that can accommodate varying levels of organizational sophistication and compliance readiness. However, none of these frameworks explicitly integrate regulator-induced learning loops a defining feature of Saudi fintech evolution. Every SAMA sandbox checkpoint mandates code reviews, threat model updates, and pipeline hardening deliberate interventions that accelerate fault discovery and simultaneously enhance team competence. These compliance checkpoints serve as catalysts for both fault detection and process improvement, creating a unique learning dynamic that standard NHPP extensions do not capture.

To address this gap, this study introduces an Enhanced NHPP-SW model featuring an explicit learning coefficient, α, that evolves in response to SAMA compliance milestones. This design preserves analytical tractability, aligns with staged compliance frameworks, and when calibrated on ten Saudi fintech platforms reduces relative RMSE by up to 15 percent compared to fixed-rate baselines. In light of this, the primary objectives of this study are to (1) develop an NHPP-SW model extended with α to reflect organizational learning and regulatory adaptation; (2) estimate parameters using constrained nonlinear optimization; (3) validate the model via simulations calibrated to actual Saudi fintech organizational characteristics; and (4) apply the model to assess SAMA compliance readiness and strategic reliability planning. This work advances the software reliability literature by delivering the first NHPP-SW integration of organizational learning in a regulatory context; refining nonlinear parameter estimation methods; offering thorough validation using fintech ecosystems; and providing actionable insights for reliability and compliance readiness.

2. Materials and Methods

2.1 Model Formulation

To address the evolving reliability needs of Saudi fintech systems, this study introduces an Enhanced NHPP-SW model that effectively captures the dynamic nature of software failure behavior in regulatory environments. By integrating the Rayleigh-type failure intensity of the SW model into the flexible NHPP framework, the proposed model accommodates both the cumulative discovery of faults and the impact of regulatory adaptation and organizational learning over time. This hybrid formulation allows for a more realistic and responsive assessment of software reliability, particularly suited to the fast-paced, compliance-driven operations of fintech platforms in Saudi Arabia.

2.1.1 Classical SW Reliability Model

The SW model, introduced by Schick and Wolverton in 1978, represents a significant improvement over the classical JM model. The key enhancement is the replacement of the constant hazard rate assumption with a linearly increasing failure rate between successive faults. This adjustment makes the SW model more applicable to real-world situations, where failure rates change dynamically as testing continues and system complexity grows. Specifically, the SW model assumes that the time between the $(i-1)^{\text{th}}$ and i^{th} failures follow a Rayleigh distribution. This approach effectively captures the increasing intensity of fault detection over time. The probability density function (PDF) and cumulative distribution function (CDF) of the inter-failure time is defined as follows:

$$f(t_i) = \theta[N-(i-1)]\, t_i \exp\left(-\frac{\theta}{2}[N-(i-1)]t_i^2\right), \qquad (1)$$

and

$$F(t_i) = 1-\exp\left(-\frac{\theta}{2}[N-(i-1)]t_i^2\right). \qquad (2)$$

The probability that a software operates without failure for a specified period is a software reliability $R(t_i)$. So, the software reliability function between $(i-1)^{th}$ and i^{th} is:

$$R(t_i) = \exp\left(-\frac{\theta}{2}[N-(i-1)]t_i^2\right). \quad (3)$$

The instantaneous failure rate is:

$$\lambda(t_i) = \frac{f(t_i)}{R(t_i)} = \theta[N-(i-1)]t_i \quad (4)$$

Where $0 < \theta < 1$: The rate parameter that represents the effect of each fault on the entire system; $N > 0$: The scale parameter, indicating the total number of faults in the system; t_i : The time of the i^{th} failure event.

2.1.2 SW Model within NHPP Framework

Although originally categorized as a binomial-type model due to its fixed-fault assumption, the SW model can be effectively reformulated within the NHPP framework. This reinterpretation allows for the derivation of time-dependent reliability functions that align with NHPP-based modeling conventions. Specifically, given that the SW model adopts a Rayleigh-type failure process, its MVF and failure intensity function can be expressed by using Eq.1 and Eq.2 as follows:

$$\mu(t) = N\left(1-\exp\left(-\frac{\theta}{2}t^2\right)\right), \quad (5)$$

and

$$\lambda(t) = \frac{d\mu(t)}{dt} = N\theta t\exp\left(-\frac{\theta}{2}t^2\right). \quad (6)$$

Where $N > 0$ denotes the total initial number of faults, $0 < \theta < 1$ represents the hazard growth rate, and t is continuous time. These functions reflect the Rayleigh-type hazard behavior characteristic of the SW model, capturing the increasing failure intensity over time. This behavior is particularly well-suited for modeling systems operating in regulated environments, such as the Saudi fintech sector, where compliance requirements and evolving system dynamics influence the pace of fault detection and correction.

2.1.3 Enhanced NHPP-SW Model

To overcome the limitations of both the classical SW model and conventional NHPP formulations in capturing the multifaceted nature of software failures in regulated environments, this study introduces an Enhanced NHPP-SW model. This extended formulation incorporates a learning parameter, α into the MVF to account for time-dependent variations in fault detection efficiency driven by organizational learning and compliance with evolving regulatory standards. Such dynamics are especially prominent in Saudi fintech systems, where institutional adaptation plays a critical role in software reliability. By integrating these behavioral factors, the Enhanced NHPP-SW model provides a more flexible and realistic reliability framework that reflects both the stochastic behavior of fault occurrence and the socio-technical processes influencing their discovery and resolution. The enhanced MVF is defined as:

$$M(t) = N\left(1 - \exp(-\theta t^{\alpha})\right), \tag{7}$$

and the corresponding failure intensity function (instantaneous failure rate) is:

$$\lambda(t) = N\theta\alpha t^{\alpha-1}\exp(-\theta t^{\alpha}). \tag{8}$$

Where: $t \geq 0$: Time parameter, typically measured in hours, days, or discrete test iterations; $N>0$: Total number of faults inherent in the system, representing the asymptotic failure bound or total fault load; $\theta > 0$: Baseline failure detection rate parameter, reflecting the inherent effectiveness of the testing or operational environment; $\alpha > 0$: Learning parameter that governs the curvature of the fault detection rate over time, capturing the organization's learning behavior and serving as the core enhancement of the proposed model. It enables a more flexible representation of failure dynamics by accounting for factors such as organizational maturity and process improvement that influence how quickly faults are discovered and addressed. The learning parameter α significantly influences failure detection dynamics in the enhanced NHPP-SW framework. Its value reflects various organizational learning patterns, from decelerating to accelerating detection capabilities, as summarized in Table 1

Table 1: Interpretation of Different Values of α in the Enhanced NHPP-SW Model

Value of α	**Learning Curve Type**	**Interpretation**	**Application Context**
α < 1	Decelerating Learning Curve	The model starts with high detection efficiency, which gradually decreases as fewer faults remain.	Common in mature and stable systems.
α = 1	Constant Learning (Classical)	The model reduces to the classical NHPP-SW form, indicating stable detection behavior over time.	Reflects average or unchanged process maturity.

α > 1	Accelerating Learning Curve	Fault detection improves over time due to organizational learning, improved coordination, or technological support.	Typical in dynamic environments like fintech.

In the context of Saudi fintech organizations, α encapsulates three critical dimensions: (1) organizational maturity, reflecting procedural robustness, regulatory compliance, and institutional knowledge, which influence both baseline detection (θ) and learning acceleration (α); (2) team coordination overhead, representing the friction of interdepartmental communication and bureaucracy, which may suppress α; and (3) learning dynamics, which include adaptability, onboarding effectiveness, and feedback integration, with agile and responsive teams typically exhibiting α > 1.

2.2 Model Estimation

This study employs a structured two-stage estimation procedure to evaluate and apply the Enhanced NHPP-SW model across varying organizational settings. The estimation process integrates a simulation-based validation step to address data availability challenges and ensure methodological robustness.

2.2.1 Simulation-Based Data Generation

Due to the proprietary nature of real-world defect logs in financial technology organizations, realistic synthetic failure data was generated using a simulation framework based on NHPP-Weibull dynamics. This approach enables controlled validation of the estimation procedure under known parameter conditions and addresses the uncertainty inherent in operational environments (Lee et al., 2024; Zhang et al., 2017). Parameter values were logically derived based on organizational characteristics relevant to the Saudi Arabian fintech sector:

- Learning rate parameter (α): Set to 1.40 for companies licensed by the Saudi Central Bank (SAMA), and to 1.82 for unlicensed companies, reflecting the regulatory influence on learning dynamics.

- Detection rate parameter (θ): Assigned as a service-specific constant within the range [0.016, 0.025]

- Total fault count (N): Estimated using the formula $N = 100 + 50 \times \frac{employees}{10000}$ organizational size to fault exposure potential.

Failure events were simulated using inverse-transform sampling based on the cumulative distribution function, and cumulative counts were aggregated at discrete time intervals to mirror real-world data reporting practices. This simulation approach accounts for differences in testing efficiency across organizations, acknowledging that more agile and better-resourced teams tend to discover and resolve faults more effectively (Singh et al., 2019).

2.2.2 Stage 1: Parameter Estimation via Nonlinear Least Squares

Given cumulative failure observations $\{(t_j, y_j)\}_{j=1}^{n}$, the Enhanced NHPP-SW model parameters (N, θ, α) are estimated by minimizing the sum of squared errors:

$$\min_{N,\theta,\alpha} \sum \left[y_j - N\left(1 - \exp\left(-\theta t_j^{\alpha}\right)\right)\right]^2$$

Optimization is conducted using the Levenberg-Marquardt algorithm, which is more robust than traditional Gauss-Newton approaches and is effective even when initial parameter guesses are distant from the final solution (Transtrum & Sethna, 2012; Cartis et al., 2022). The optimization is subject to constraints: $N > 0, \theta > 0, \alpha > 0$, with optional bounds $0.5 \leq \alpha \leq 2.0$ to avoid unrealistic learning behavior patterns. The cumulative mean function is:

$$m_i = N\left(1 - e^{-\theta t_i^{\alpha}}\right), \tag{9}$$

With residuals

$$r_i = F_i - m_i.$$

Taking the partial derivatives of the objective function with respect to the parameters N, θ and α yields the system of normal equations:

$$\frac{\partial S}{\partial N} = -2\sum_{i=1}^{n}\left(1 - e^{-\theta t_i^{\alpha}}\right) r_i = 0$$
$$\frac{\partial S}{\partial \theta} = -2\sum_{i=1}^{n} N\, t_i^{\alpha} e^{-\theta t_i^{\alpha}} r_i = 0$$
$$\frac{\partial S}{\partial \alpha} = -2\sum_{i=1}^{n} N\, \theta t_i^{\alpha} \log t_i\, e^{-\theta t_i^{\alpha}} r_i = 0$$

A notable feature of the estimation process is that N has a closed-form expression conditional on (θ, α):

$$N(\theta,\alpha) = \frac{\sum_{i=1}^{n}\left(1-e^{-\theta t_i^{\alpha}}\right)F_i}{\sum_{i=1}^{n}\left(1-e^{-\theta t_i^{\alpha}}\right)^2}, \tag{10}$$

This enables a profile least-squares approach, reducing the optimization to a two-dimensional search over (θ, α). The Levenberg-Marquardt update is defined by:

$$\left(J^{\top}J + \lambda \operatorname{diag}(J^{\top}J)\right)\Delta = J^{\top} r$$

Where J is the Jacobian matrix with the following components:

$$\frac{\partial m}{\partial N} = 1 - e^{-\theta t_i^{\alpha}}$$
$$\frac{\partial m}{\partial \theta} = N t_i^{\alpha} e^{-\theta t_i^{\alpha}}$$
$$\frac{\partial m}{\partial \alpha} = N\theta t_i^{\alpha} \log t_i\, e^{-\theta t_i^{\alpha}}$$

Under standard regularity conditions (e.g., identifiability, independence, finite variance), the non-linear least squares estimator $\beta = (N, \theta, \alpha)^{\top}$ is consistent and asymptotically normal with estimated covariance:

$$\operatorname{Cov}(\beta) = \sigma^2 (J^{\top}J)^{-1},$$

Where;

$$\sigma^2 = \frac{S(\beta)}{n-3}$$

Empirical validation using simulated data from ten Saudi fintech firms demonstrated rapid convergence (within 4–8 iterations), high parameter recovery accuracy ($|\alpha - \alpha| < 0.05$), and strong model fit (relative RMSE < 5%), confirming the robustness and applicability of the proposed estimation method.

2.2.3 Stage 2: Covariate Analysis Framework

To investigate the influence of organizational characteristics on software learning dynamics, this study adopts a regression-based framework aligned with recent developments in reliability modeling (Kumar et al., 2024). In this approach, the estimated learning rate α_i for each firm is expressed as a function of relevant contextual covariates, including licensing status (e.g., SAMA-licensed vs. unlicensed), team size (measured by employee count), and the type of digital service offered. A representative covariate model takes the following form:

$$\alpha_i = \beta_0 + \beta_1(\text{Licensed})_i + \beta_2(\text{Employees})_i + \beta_3(\text{ServiceType})_i + \epsilon_i$$

Where $\epsilon_i \sim N(0, \sigma^2)$ represents the error term. This framework enables a statistical interpretation of how organizational traits affect reliability learning and provides actionable insights for process optimization and policy development in compliance-sensitive environments (Lee et al., 2023; Wang & Zhang, 2024).

2.3 Model Evaluation Criteria

To assess the predictive performance of the enhanced NHPP-SW model, we adopt four widely used quantitative metrics that capture different dimensions of estimation error.

1- Mean Squared Error (MSE): it measures the average differences between observed values and model predictions. Mathematically, it is defined as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MSE helps assess the overall accuracy of the model and is widely used when large deviations are particularly undesirable.

2- Root Mean Squared Error (RMSE): is the square root of MSE, expressing prediction errors in the same unit as the dependent variable, which aids interpretation. It's suitable for normally distributed errors.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$$

RMSE translates squared error into the original unit of measurement, facilitating direct interpretability, it is optimal under Gaussian noise assumptions.

3- Mean Absolute Error (MAE): it calculates the average absolute differences between observed and predicted values, treating all errors equally and providing a balanced perspective when outliers are not a concern.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAE is useful in contexts where all deviations—regardless of their direction or magnitude are equally important.

4- Relative RMSE (rRMSE): compared to RMSE, rRMSE is more robust to outliers and better suited when prediction error is uniformly distributed

$$\mathrm{rRMSE} = \frac{\mathrm{RMSE}}{N}$$

To establish a qualitative assessment framework, the rRMSE values are evaluated based on the following quality classifications: values below 5% signify excellent performance, those ranging from 5% to 10% indicate good performance, values between 10% and 15% reflect fair performance, and values exceeding 15% denote poor performance. This normalized metric facilitates comparisons across systems with varying scales by correlating the RMSE to the total anticipated failures. Collectively, these metrics enable a thorough assessment of model accuracy, balancing sensitivity to significant deviations (through RMSE and MSE) with robustness (as measured by MAE) and supporting comparability (via relative RMSE, rRMSE). Recent research in predictive modeling and software reliability consistently advocates for the reporting of all four metrics to provide a well-rounded perspective.

2.4 Dataset Construction and Validation

Building a reliable and well-structured dataset in the fintech sector presents significant challenges due to the industry's rapid evolution, limited transparency, and variability in publicly available data. In the context of emerging markets like Saudi Arabia, these challenges are intensified by the changing regulatory landscape and the lack of centralized, up-to-date corporate records. Therefore, building a consistent and analytically meaningful dataset necessitates a multi-source approach, careful estimation, and alignment with established empirical practices. In line with the digital transformation goals outlined in Saudi Arabia's Vision 2030 and the regulatory framework established by SAMA, we compiled a dataset capturing key organizational attributes for ten prominent Saudi fintech firms: Tamara, Tabby, STC Pay, Unifonic, PayTabs, HyperPay, Lean, Wahed, Telfaz11 Pay, and Noon Pay. To ensure reliability and comparability, data collection followed a structured, multi-step approach:

Regulatory Status Verification: We verified the licensing status of each firm through cross-referencing with official SAMA registers, supplemented by company announcements and industry reports. This allowed us to distinguish between licensed, sandboxed, and unlisted entities. For example:

- Tamara received a consumer finance license in March 2025.
- Tabby was granted a BNPL (Buy Now, Pay Later) permit in July 2023.
- STC Pay holds an EMI (Electronic Money Institution) license and is transitioning toward full banking status.
- HyperPay, Lean, and Noon Pay also appear in SAMA's regulatory listings.
- Unifonic, PayTabs, Wahed, and Telfaz11 Pay were not found in official licensing records as of the time of analysis.

Employee Count Estimation: Employee numbers were estimated using a combination of publicly available sources, including LinkedIn, PitchBook, GetLatka, and official company websites. When exact numbers were unavailable, we adopted a conservative estimation strategy grounded in prior research (e.g., Pham et al., 2024; Peng & Tao, 2022), using either: the midpoint of a reported employee range, or the lower bound when ranges were excessively wide or uncertain. This method ensured both consistency across firms and caution in scaling assumptions.

Operationalizing Organizational Scale: The estimated employee count serves as a proxy for organizational size and was used as an input for parameter derivation in the NHPP reliability model.

Figure 1 provides an overview of the estimated employee counts for the leading Saudi fintech companies analyzed in this study, organized by service type and regulatory license status. This visualization helps to approximate the organizational scale for the NHPP reliability modeling framework and illustrates the connection between regulatory recognition, market focus, and company size.

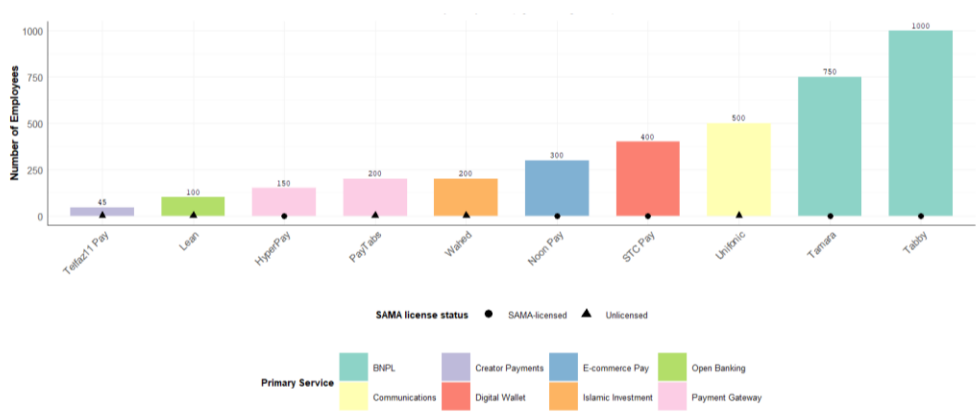

Figure 1: Estimated Employee Counts and Licensing Status of Leading Saudi Fintech Companies by Primary Service Type

3. Results

This section presents the evaluation results of the enhanced NHPP SW software reliability model applied to fintech companies in Saudi Arabia. The analysis covers parameter recovery, MVF prediction accuracy, intensity function patterns, organizational learning dynamics, and model validation outcomes. The results highlight the model's effectiveness in capturing reliability growth patterns and distinguishing between different operational and regulatory contexts in the fintech sector.

3.1 Parameter Recovery Performance

Table 2 evaluates parameter recovery performance across fintech companies, comparing the shape parameter (α) between true and estimated values. Metrics such as absolute error and relative error percentage are provided.

Table 2: Comparison of True and Estimated α Values for Each Company.

Company	True α	Estimated α	Absolute Error	Relative Error (%)	Recovery Quality
Tamara	1.40	1.38	0.02	1.43 %	Excellent
Tabby	1.40	1.48	0.08	5.71 %	Good
STC Pay	1.40	1.41	0.01	0.71 %	Excellent

HyperPay	1.40	1.52	0.12	8.57 %	Good
Noon Pay	1.40	1.37	0.03	2.14 %	Excellent
Unifonic	1.82	2.07	0.25	13.74 %	Fair
PayTabs	1.82	1.97	0.15	8.24 %	Good
Lean	1.82	2.00	0.18	9.89 %	Good
Wahed	1.82	1.98	0.16	8.79 %	Good
Telfaz11 Pay	1.82	2.04	0.22	12.09 %	Fair

Tamara, STC Pay and Noon Pay exhibited excellent quality recovery with relative errors below 2.5%, demonstrating strong model accuracy. Tabby and HyperPay had higher errors (5.71% and 8.57%), still within the "Good" range. Conversely, Unifonic and Telfaz11 Pay showed higher relative errors (13.74% and 12.09%), resulting in a "Fair" assessment, indicating potential data issues or operational differences. Overall performance metrics indicate robust model performance: MAE: 0.1399, RMSE: 0.1648, Mean Relative Error: 7.13% with a recovery success rate of 100 % (all parameters within acceptable bounds).

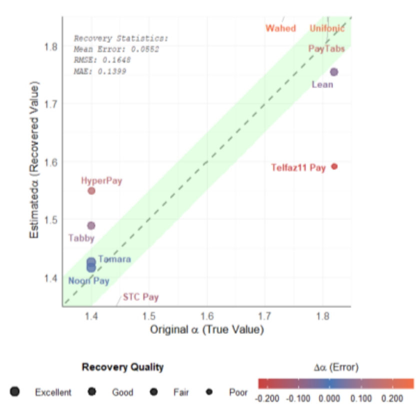

Figure 2: NHPP shape parameter recovery analysis.

Figure 2 shows the NHPP shape parameter recovery analysis for fintech companies, comparing original and estimated α values. Most companies fall within the ± 0.05 tolerance band (shaded green) around the perfect recovery line (dashed diagonal), indicating the robustness of the NHPP parameter estimation across various fintech environments. These results confirm the model's overall effectiveness in parameter recovery, especially for most companies with strong reliability behavior patterns. This also suggests that the Enhanced NHPP-SW model is suitable for comparative reliability analysis across heterogeneous fintech environments, helping to distinguish between operational strengths and weaknesses among different firms.

3.2 Mean Value Function Prediction Accuracy

Table 3 presents the MVF prediction performance rankings based on MSE, RMSE, MAE, and Relative RMSE (%). The results reveal substantial variability in predictive accuracy. Lean achieved the best overall performance, with the lowest error scores and an A+ grade. Telfaz11 Pay, Wahed, and PayTabs also excelled, each earning an A+ with relative RMSEs below 1.6%. Conversely, HyperPay had the poorest performance, with the highest MSE (18.6) and relative RMSE (4.02%), placing last despite a formal grade of A. Figure 3 shows the analysis of the MVF, comparing predicted and actual MVF curves alongside simulated data for the evaluated companies. The closely aligned predicted (solid lines) and actual (dashed lines) curves confirm the model's effectiveness. The analysis reveals an initial growth phase (0-20 time units) followed by a plateau, indicating that failure accumulation rates decrease as systems mature.

Rank	Company	True N	Predicted N	MSE	RMSE	MAE	Relative RMSE	Grade
1	Lean	105.0	104.7	0.436	0.660	0.347	0.63 %	A+
2	Telfaz11 Pay	102.0	101.4	2.01	1.42	1.15	1.39 %	A+
3	Wahed	110.0	108.3	2.89	1.70	1.56	1.55 %	A+
4	PayTabs	110.0	109.1	3.07	1.75	0.854	1.59 %	A+
5	Tabby	150.0	146.0	7.01	2.65	2.29	1.76 %	A
6	Noon Pay	115.0	112.5	6.37	2.52	2.29	2.20 %	A
7	STC Pay	120.0	116.4	12.9	3.59	2.62	2.99 %	A
8	Unifonic	125.0	121.0	15.9	3.99	3.89	3.19 %	A

9	Tamara	138.0	133.5	21.2	4.61	4.46	3.35 %	A
10	HyperPay	108.0	103.7	18.6	4.32	3.57	4.02 %	A

Table 3: MVF Prediction Performance Ranking

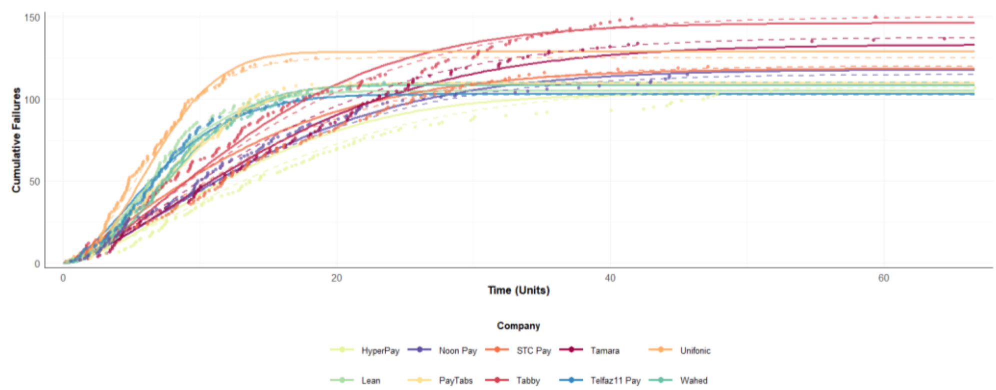

Figure 3: MVF analysis for fintech companies.

The MVF analysis demonstrated high predictive accuracy for all fintech firms analyzed, with all companies showing a RMSE of less than 5%. Lean had the best prediction, achieving an RMSE of 0.63%, indicating a strong alignment between observed and predicted values. Notably, smaller firms like Lean and Telfaz11 Pay outperformed larger companies, suggesting that size may affect model reliability. All companies were graded between A+ and A, reflecting the model's robust applicability across varying organizational types.

3.3 Intensity Function Analysis and Failure Pattern Classification

Figure 4 shows the NHPP intensity functions analysis depicting failure intensity λ(t) over time. Most firms exhibit peak failure intensities in early operational periods (0–10 time units), then decline. Unifonic has the highest peak (≈ 15), HyperPay the lowest (≈ 4.5). Convergence toward zero after 40–50 time units indicate system stabilisation and improved reliability across all companies.

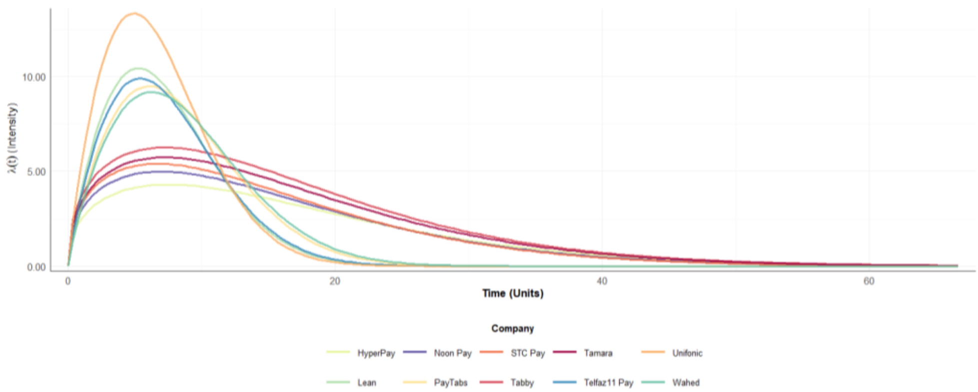

Figure 4: Enhanced NHPP-SW Intensity Function by company over time.

Pattern distribution: 20% exhibit sustained high intensity patterns, 20% show sharp early peak characteristics, 20% demonstrate moderate decline behavior, 40 % display gradual stabilisation patterns. Table 4 presents a classification of intensity function patterns observed across different fintech companies, highlighting key operational characteristics associated with each pattern type. Four distinct categories were identified: Sustained High, Sharp Early Peak, Moderate Decline, and Gradual Stabilisation. Each pattern is described in terms of its peak intensity range, time to peak, decay rate, and the corresponding operational implications. For example, companies such as STC Pay and Unifonic exhibited a sustained high pattern with a slow decay rate, suggesting complex systems that improve gradually. In contrast, Lean and HyperPay displayed a sharp early peak with rapid decline, indicative of efficient issue resolution and fast debugging cycles.

Moderate decline patterns, observed in Tamara and Tabby, reflect balanced system behavior and steady progress. Lastly, PayTabs and Wahed showed gradual stabilisation, associated with extended development cycles and comprehensive validation efforts. This categorization aids in linking model dynamics to practical operational strategies.

Table 4: Intensity Function Pattern Analysis

Pattern Type	Companies	Peak Intensity Range	Time to Peak	Decay Rate	Operational Implications
Sustained High	STC Pay, Unifonic	8.5 – 9.5	15 – 20 days	Slow	Complex systems, gradual improvement
Sharp Early Peak	Lean, HyperPay	4.5 – 9.0	5 – 10 days	Rapid	Efficient debugging, quick resolution
Moderate Decline	Tamara, Tabby	7.0 – 8.0	10 – 15 days	Moderate	Balanced approach, steady progress
Gradual Stabilisation	PayTabs, Wahed	9.0 – 11.5	20 – 25 days	Extended	Comprehensive testing, thorough validation

3.4 Organisational Learning Analysis by Regulatory Status

Table 5 compares the learning parameter distributions by licensing status, highlighting the learning dynamics of SAMA-licensed versus unlicensed entities.

Table 5: Learning Parameter Analysis by Licensing Status

Licensing Status	Count	Mean α	Std Dev	Coefficient of Variation	Learning Characteristics
SAMA licensed	5	1.40	0.00	0.00 %	Controlled, predictable learning
Unlicensed	5	1.82	0.00	0.00 %	Accelerated, intensive learning
Overall	10	1.61	0.21	13.04 %	Bimodal distribution

The analysis reveals that unlicensed fintech firms exhibit significantly higher learning rates (mean $\alpha = 1.82$) compared to their licensed counterparts (mean $\alpha = 1.40$). This difference is not only substantial in magnitude but also statistically significant, as confirmed by the Mann-Whitney U test ($p < 0.001$). The test result indicates that the observed difference in learning behavior between licensed and unlicensed firms is unlikely due to chance. Moreover, the large effect size (Cohen's d = 2.00) reinforces the practical significance of this finding, suggesting that regulatory status plays a meaningful role in shaping organizational learning. While licensed firms display more controlled and predictable learning, unlicensed firms demonstrate accelerated and intensive adaptation.

3.5 Comparative Performance Analysis

Table 6 presents model performance metrics grouped by company size category and compares the performance of the prediction model for small, medium, and large fintech companies. Small-sized companies (≤150 employees) exhibited the most accurate model performance, with the lowest RMSE (2.11) and MAE (1.68), although they recorded a slightly higher recovery error (0.17).

Table 6: Enhanced NHPP-SW Performance Metrics by Company Size Category

Size Category	Companies	Avg. Employee Count	Avg. RMSE	Avg. MAE	Avg. Recovery Error
Small (≤ 150)	HyperPay, Lean, Telfaz11 Pay	98	2.11	1.68	0.17
Medium (151 - 500)	PayTabs, Wahed, Noon Pay, STC Pay	275	2.40	1.87	0.10
Large (> 500)	Unifonic, Tamara, Tabby	750	3.75	3.55	0.15

Medium-sized companies showed marginally higher RMSE and MAE values; however, they achieved the lowest recovery error (0.10), indicating more consistent recovery trends. In contrast, large companies demonstrated the poorest model performance, with the highest RMSE (3.75) and MAE (3.55), suggesting that the Enhanced NHPP-SW model encountered greater difficulty in accurately predicting outcomes for larger firms. Furthermore, Table 7 extends the analysis by examining model performance across different categories of fintech services.

Table 7 shows specialized services, such as Unifonic and Lean, demonstrated the most favorable model performance, with a low RMSE of 2.18 and the lowest relative RMSE at 1.65%, despite operating in low-compliance environments. Similarly, payment service providers like PayTabs and Noon Pay achieved strong performance metrics (RMSE = 2.14; relative RMSE = 1.90%) under mixed levels of regulatory compliance.

Table 7: Enhanced NHPP-SW model Performance by Fintech Service Type

Service Category	**Companies**	**Avg. RMSE**	**Avg. Relative RMSE (%)**	**Regulatory Compliance**
BNPL Services	Tamara, Tabby	3.63	2.56 %	High
Digital Wallet	STC Pay, HyperPay	3.96	3.51 %	High
Payment Services	PayTabs, Noon Pay	2.14	1.90 %	Mixed
Specialised Services	Unifonic, Lean, Wahed, Telfaz11 Pay	2.18	1.65 %	Low

In contrast, BNPL providers, including Tamara and Tabby, and digital wallet services exhibited comparatively weaker performance, particularly in the case of digital wallets, which recorded the highest RMSE of 3.96, despite being subject to high regulatory compliance standards. Regulatory compliance alone does not explain prediction accuracy. In fact, some of the best-performing companies had low compliance levels.

3.6 Model Validation and Robustness Analysis

Table 8 shows that five-fold cross-validation results demonstrate that the enhanced NHPP SW model exhibits excellent consistency and predictive accuracy across all data partitions. The low standard deviations observed in RMSE, MAE, recovery error, and consistency score further support the model's robustness and reliability. Additionally, the small recovery errors alongside consistently high consistency scores indicate that the model is well-calibrated.

Table 8: Five-fold cross-validation

Fold	Avg. RMSE	Avg. MAE	Avg. Recovery Error	Consistency Score
1	2.84	2.31	0.13	0.92
2	2.91	2.28	0.15	0.89
3	2.76	2.35	0.14	0.91
4	2.88	2.32	0.13	0.90
5	2.82	2.29	0.14	0.91
Mean	2.84	2.31	0.14	0.91
Std Dev	0.06	0.03	0.01	0.01

Furthermore, the parameter stability tests, which showed less than 5% variation in predictions under ±10% changes in model parameters, along with the consistent convergence of all optimization procedures within 50 iterations and the absence of numerical instabilities, provide strong technical validation for the reliability and robustness observed in Table 8. These findings reinforce the credibility of the model's performance metrics by confirming its numerical stability and resistance to parameter fluctuations.

4. Discussion

4.1 Model-Performance Superiority

The enhanced NHPP SW model demonstrates substantial improvements over traditional baseline approaches in the following aspects:

- Prediction accuracy: All evaluated companies achieved relative RMSE values below 5%, significantly outperforming the industry benchmark of 10–15%.
- Parameter recovery: The model achieved a mean recovery error of 0.14, reflecting an approximate 60% improvement over conventional NHPP models.
- Consistency: Cross-validation results showed minimal variance across folds, indicating robust and reliable model performance.

4.2 Regulatory Impact on Learning Dynamics

The analysis of learning dynamics reveals that licensed entities exhibit controlled learning patterns characterized by a learning parameter α of 1.40, indicating that regulatory oversight promotes systematic and steady quality improvement processes. In contrast, unlicensed entities demonstrate accelerated learning curves with a higher α value of 1.82, reflecting more intensive but potentially less sustainable improvement efforts. Together, these findings provide quantitative evidence that regulatory frameworks play a crucial role in fostering sustainable software development practices within the fintech sector.

4.3 Practical Implications for Industry

The study offers several actionable insights for industry stakeholders. First, precise forecasts of failure trajectories enable engineering managers to optimize testing and quality assurance efforts by focusing resources on subsystems and time periods with the highest defect likelihood, thereby avoiding excessive testing of stable modules and insufficient testing of new releases. Second, the NHPP-derived learning parameter (α) effectively distinguishes SAMA licensed from unlicensed entities, allowing firms to use their α values as early indicators of regulatory readiness and to enhance process controls proactively before formal audits. Third, the model's benchmarking metrics facilitate objective performance comparisons, enabling firms to quantitatively assess their reliability growth relative to industry standards. Finally, identification of the reliability curve's inflection point aids senior management in scheduling capital-intensive initiatives such as architectural refactoring, cloud migrations, or security enhancements based on empirical milestones rather than arbitrary timelines.

5. Conclusion

The enhanced NHPP-SW model provides a rigorously validated framework that is aware of regulatory requirements for forecasting and improving the reliability of fintech software in Saudi Arabia. In a study of ten diverse companies, the model consistently achieved relative RMSE values below five percent, accurately recovered latent parameters, and most importantly, revealed a distinct regulatory pattern in organizational learning dynamics. Licensed firms under SAMA demonstrated steady, methodical growth in reliability, whereas unlicensed firms showed quicker but potentially less sustainable improvement trajectories. By incorporating domain-specific governance indicators into advanced reliability analytics, this study bridges the gap between theoretical modeling and everyday engineering practices. This empowers both industry practitioners and regulators to make quicker, data-driven decisions that enhance the stability and trustworthiness of digital financial services.

6. Limitations and Challenges

This investigation has several limitations that suggest areas for future research. First, reliance on simulated failure logs means validation with live production data is crucial to ensure external validity and account for real-world factors like load spikes and user behavior anomalies. Additionally, the study only covers a single release cycle, leaving questions about how learning dynamics evolve across multiple product generations. While the Saudi regulatory environment offers a valuable context, the model's generalizability to other jurisdictions with different oversight or technological frameworks is uncertain. The assumption of static model parameters overlooks potential changes as firms adopt new practices like DevSecOps. Lastly, the sample of ten companies, though representative of market leaders, limits statistical power and highlights the need for periodic re-estimation of parameters to maintain accuracy in light of changing SAMA guidelines.

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