Griya Journal of Mathematics Education and Application
Volume 6 Nomor 2, Juni 2026
e-ISSN 2776-124X||p-ISSN 2776-1258
https://mathjournal.unram.ac.id/index.php/Griya/index

Modeling online loan risk dynamics with SEIQRL, regulation, and financial literacy analysis in Indonesia

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Abstrak
Penelitian ini mengkaji dinamika perilaku pinjaman online berisiko di Indonesia menggunakan model matematika SEIQRL. Model ini memperluas pendekatan SEIR dengan menambahkan kompartemen Karantina (Q) dan Melek Finansial (L) untuk merepresentasikan intervensi regulasi dan literasi keuangan. Tujuan penelitian adalah membangun model SEIQRL, menganalisis titik keseimbangan bebas risiko, menghitung bilangan reproduksi dasar (R_0), serta mengevaluasi pengaruh regulasi dan literasi keuangan terhadap penyebaran perilaku pinjaman online berisiko. Metode yang digunakan adalah pendekatan kuantitatif berbasis pemodelan matematika dan simulasi numerik dengan Wolfram Mathematica. Hasil menunjukkan bahwa skenario dasar menghasilkan nilai $R_0 = 6{,}1538$, yang mengindikasikan bahwa perilaku pinjaman online berisiko dapat menyebar kuat dalam populasi. Skenario regulasi kuat dan literasi kuat masing-masing menurunkan risiko, namun belum sepenuhnya mengendalikan penyebaran. Skenario gabungan regulasi dan literasi menghasilkan nilai $R_0 = 0{,}8696$, yang berarti risiko dapat dikendalikan karena $R_0 < 1$. Temuan ini menunjukkan bahwa pengendalian pinjaman online berisiko tidak dapat hanya mengandalkan pembatasan akses atau pemblokiran layanan, tetapi literasi keuangan dini harus dijadikan strategi preventif utama. Model SEIQRL ini dapat mendukung analisis kebijakan pengendalian risiko pinjaman online di Indonesia.

Kata Kunci: pinjaman online; SEIQRL; regulasi; literasi keuangan; bilangan reproduksi dasar

Abstract
This study examines the dynamics of risky online lending behavior in Indonesia using the SEIQRL mathematical model. The model extends the SEIR approach by adding Quarantined (Q) and Literate (L) compartments to represent regulatory intervention and financial literacy. This study aims to construct the SEIQRL model, analyze the risk-free equilibrium point, calculate the basic reproduction number (R_0), and evaluate the effects of regulation and financial literacy on the spread of risky online lending behavior. The method uses a quantitative approach based on mathematical modeling and numerical simulation with Wolfram Mathematica. The results show that the baseline scenario produces an R_0 value of 6.1538, indicating that risky online lending behavior can spread strongly within the population. Strong regulation and strong literacy scenarios reduce the risk, but they do not fully control its spread. The combined regulation and literacy scenario produces an R_0 value of 0.8696, meaning the risk can be controlled because $R_0 < 1$. These findings show that controlling risky online lending cannot rely only on access restrictions or service blocking. Early financial literacy must also serve as a preventive strategy. The SEIQRL model can support policy analysis for controlling online lending risks in Indonesia.

Keywords: online lending; SEIQRL; regulation; financial literacy; basic reproduction number

1. INTRODUCTION

The transformation of digital financial services in Indonesia has expanded public access to funding sources. One of the rapidly growing services is online lending or fintech lending, formally known as Information Technology-Based Peer-to-Peer Lending Services (LPBBTI). As of January 31, 2025, there were 97 licensed LPBBTI operators or fintech peer-to-peer lending platforms in Indonesia (Financial Services Authority [OJK], 2025). This indicates that online lending has become a vital component of the national digital financial ecosystem.

However, increased access to financial services has not been fully accompanied by adequate risk awareness. The 2024 National Survey on Financial Literacy and Inclusion shows that Indonesia's financial inclusion index stands at 75.02%, while the financial literacy index is at 65.43% (OJK & Central Statistics Agency [BPS], 2024). This gap indicates that while the public is increasingly able to use digital financial services, they are not yet fully capable of understanding the risks associated with interest rates, penalties, default, and the use of consumer debt. Consequently, online loans can shift from being a financial tool to a source of economic pressure on households.

The use of online loans is influenced not only by individual needs but also by the social environment and the digital space. App promotions, ease of application, quick approval, and the behavior of other users can encourage borrowing decisions without sound financial planning. Ho, Shi, and Zhang (2024) demonstrate the existence of peer effects in the peer-to-peer lending market, namely the influence of one borrower's behavior on the decisions and risks of other borrowers. Thus, the use of risky online loans can be understood as a process of behavioral diffusion within a population.

An epidemiological approach can be used to analyze the dynamics of this risk's spread. Zhao, Li, Wang, and Ma (2021) explain that credit risk on internet peer-to-peer lending platforms can be analyzed using complex network theory and the SEIR model. However, the conventional SEIR model remains limited because it only divides the population into susceptible, exposed, infected, and recovered groups. This model does not explicitly incorporate the role of regulatory interventions and financial literacy, even though these two aspects are crucial in the context of managing online lending risks in Indonesia.

Based on this gap, this study develops an SEIQRL model to analyze the dynamics of online loan usage. The study aims to construct the SEIQRL model, analyze the equilibrium point and the R_0 value, and evaluate the impact of regulatory interventions and financial literacy on the dynamics of high-risk online loan usage.

Several prior studies have applied epidemiological compartmental models to analyze financial risk behavior. Zhao et al. (2021) used the SEIR model combined with complex network theory to examine credit risk contagion on P2P lending platforms, and found that network topology significantly affects contagion speed. Hasan, Horvath, and Mares (2022) explored the relationship between financial sector development and wealth inequality, demonstrating that limited financial literacy exacerbates economic inequality. Gao, Zhu, and Ma (2024) extended this line of inquiry by analyzing peer effects and social network influence in online credit markets, confirming that social interactions accelerate credit risk diffusion. Furthermore, Ho, Shi, and Zhang (2024) specifically documented the ex-ante and ex-post peer effects in P2P lending, showing that herding behavior among borrowers amplifies systemic risk. Dorfleitner, Hornuf, Schmitt, and Weber (2017) provided foundational insights into the structure and risks of FinTech platforms, establishing the regulatory context for P2P lending. Despite these contributions, none of the existing models simultaneously incorporated regulatory quarantine mechanisms and financial literacy as distinct population compartments capable of modifying system dynamics from both a preventive and curative perspective.

The gap in the existing literature lies in the failure to model the dual intervention role of regulation and financial literacy as structural components of the population dynamics. Prior SEIR-based models treat recovery as a single pathway (I→R) and do not distinguish between curative regulatory enforcement (quarantine) and preventive financial education (literacy). This study addresses this gap by developing the SEIQRL model, which introduces a Quarantined (Q) compartment representing formal regulatory intervention and a Literate (L) compartment representing financial literacy as an absorbing state. The novelty of this study lies in the explicit mathematical formulation of both pathways within a single integrated compartmental system, enabling simultaneous analysis of their distinct contributions to reducing the basic reproduction number (R_0) in the Indonesian online lending context.

2. RESEARCH METHOD

This study employs a quantitative approach based on mathematical modeling. The model used is the SEIQRL compartmental model, which is derived from the SEIR epidemiological model. The population in the model is divided into six compartments: Susceptible (S), Exposed (E), Infected (I), Quarantined (Q), Recovered (R), and Literate (L). Each compartment represents an individual's status regarding the use of high-risk online loans.

The meaning of each compartment in the SEIQRL model is as follows. The Susceptible (S) compartment represents individuals who have not yet used online lending services but are at risk of being influenced by social or digital factors. The Exposed (E) compartment represents individuals who have been exposed to the influence of online lending—through social media advertisements, peer recommendations, or app promotions—but have not yet taken out a loan. The Infected (I) compartment represents individuals who are actively using high-risk online loans, characterized by borrowing behavior that exceeds repayment capacity or reliance on multiple loan platforms. The Quarantined (Q) compartment represents individuals who have been subjected to regulatory enforcement, such as account freezing, inclusion in the credit blacklist (SLIK), or platform restrictions by the Financial Services Authority (OJK). The Recovered (R) compartment represents individuals who have ceased high-risk online lending behavior, either voluntarily or as a result of completing regulatory sanctions. The Literate (L) compartment represents individuals who have attained a sufficient level of financial literacy to permanently avoid high-risk online lending, either through preventive education (from S) or through post-recovery financial training (from R). The L compartment functions as a terminal absorbing state in the system.

The research procedure follows these sequential steps: (1) identification of the problem and formulation of research objectives; (2) construction of the SEIQRL system of differential equations based on population flow assumptions; (3) determination of the risk-free equilibrium point; (4) derivation of the basic reproduction number R_0 using the Next-Generation Matrix method; (5) numerical simulation using Wolfram Mathematica with hypothetical parameter values; (6) scenario analysis comparing four policy configurations; and (7) interpretation of results and policy implications.

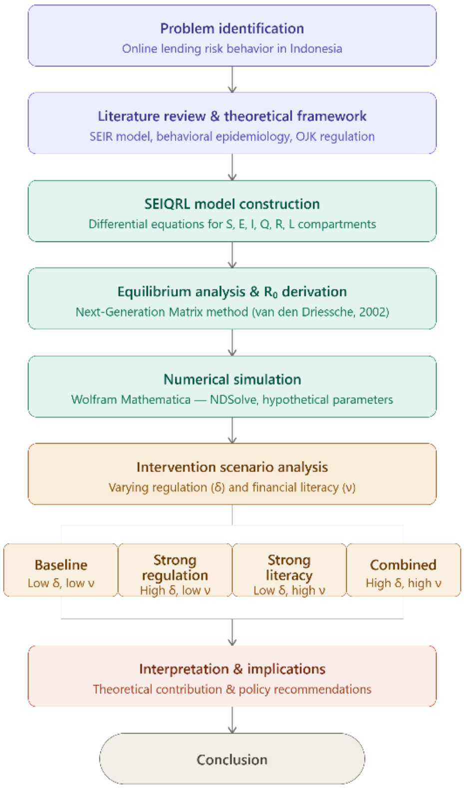

Figure 1. Research Procedure Flowchart

3. RESULT AND DISCUSSION

3.1 SEIQRL Mathematical Model

Based on the dynamics of movement between groups, the mathematical model is formulated as follows:

$$\frac{dS}{dt} = \Lambda - \beta SI - \nu S$$
$$\frac{dE}{dt} = \beta SI - \sigma E$$
$$\frac{dI}{dt} = \sigma E - (\gamma + \delta)I$$
$$\frac{dQ}{dt} = \delta I - \alpha Q$$
$$\frac{dR}{dt} = \gamma I + \alpha Q - \eta R$$
$$\frac{dL}{dt} = \nu S + \eta R$$

Tabel 1. SEIQRL Model Parameters

Parameter	Description	Academic Justification
Λ	Recruitment Rate	New individuals entering their productive years or who have recently gained access to the internet.
β	Rate of influence (S→E)	The strength of social interactions and the influence of advertising algorithms.
σ	Transition rate (E→I)	The speed at which individuals are exposed to and take out their first loan.
δ	Quarantine rate (I→Q)	Regulatory intervention (such as account restrictions by OJK/SLIK).
γ	Recovery rate (I→R)	Individuals who stop using the service on their own.
α	Rate of release from quarantine (Q→R)	The effectiveness of the restructuring period or sanctions on user behavior.
ν	Early literacy rate (S→L)	Preventive education programs that provide permanent immunity.
η	Rate of advanced literacy (R→L)	Transformation of individuals who have borrowed into financial literacy.

3.2 Risk-Free Equilibrium Point (P_0)

The risk-free equilibrium point describes the condition when the community ecosystem is free from the spread of the loan app hazard, so that $E^* = 0$, $I^* = 0$, and $Q^* = 0$. Based on the disappearance of this infected compartment, the equilibrium values are obtained:

$$\Lambda - \nu S = 0 \Rightarrow S^* = \frac{\Lambda}{\nu}$$

$$E^* = 0, \quad I^* = 0, \quad Q^* = 0, \quad R^* = 0$$

Critical analysis of compartment L behavior: Under risk-free conditions ($S^* = \Lambda/\nu$ and $R^* = 0$), the rate of change equation for the Literate compartment becomes:

$$\frac{dL}{dt} = \nu\left(\frac{\Lambda}{\nu}\right) + \eta(0) = \Lambda$$

Since $\Lambda > 0$, then $dL/dt = \Lambda \neq 0$. The L compartment acts as an "absorbing state" that increases linearly with time($L(t) \approx \Lambda t$). Therefore, the stability of the system is centered on the five-dimensional subsystem (S, E, I, Q, R).

3.3 Decrease in the Basic Reproduction Number (R_0)

The Basic Reproduction Number (R_0) is determined using the Next-Generation matrix approach on the risk-carrying compartments (E, I, Q). The new infection transmission matrix (F) and the compartment transition matrix (V) at point P_0 are:

$$F = \left[0, \frac{\beta\Lambda}{\nu}, 0;\ 0, 0, 0;\ 0, 0, 0\right]$$

$$V = [\sigma, 0, 0;\ -\sigma, \gamma + \delta, 0;\ 0, -\delta, \alpha]$$

The R_0 value is obtained from the spectral radius (dominant eigenvalue) of the matrix $K = FV^{-1}$:

$$R_0 = \rho(K) = \frac{\beta\Lambda}{[\nu(\gamma + \delta)]}$$

This exact formula for R_0 mathematically proves that purely curative interventions through the recovery rate (γ) will never be strong enough to reduce the risk unless accompanied by an increase in the regulatory quarantine rate (δ) and the inclusion of early financial literacy (v) as a denominator multiplier.

3.4 Analysis of Mathematical Form Consistency

Based on an examination of the model in the PDF draft, the initial mathematical form is consistent with the SEIQRL system used in the simulation. The model contains six differential equations for the S, E, I, Q, R, and L compartments, with the same form as the Wolfram Mathematica code used in the simulation section.

The decline in the basic reproduction number is also consistent with the model, namely:

$$R_0 = \frac{\beta\Lambda}{[\nu(\gamma + \delta)]}$$

3.5 Numerical Simulation of the SEIQRL Model

Numerical simulations were conducted to examine the dynamics of each compartment in the SEIQRL model. The system was solved using Wolfram Mathematica with the NDSolve function. The parameter values used in the simulations are hypothetical, intended to illustrate the dynamic patterns of risky online loan usage, rather than representing empirical estimates.

Tabel 2. Simulation Parameter Values

Parameter	Value	Description
Λ	20	Rate of recruitment of new individuals
β	0.0008	Rate of social and digital influence
σ	0.18	Rate of transition from exposure to high-risk user
γ	0.08	Rate of spontaneous recovery
δ	0.05	Regulatory quarantine rate
α	0.10	Release rate from quarantine
ν	0.02	Early literacy rate
η	0.04	Advanced literacy rate

The initial simulation values are defined as follows: S(0) = 900, E(0) = 60, I(0) = 30, Q(0) = 5, R(0) = 5, L(0) = 0.

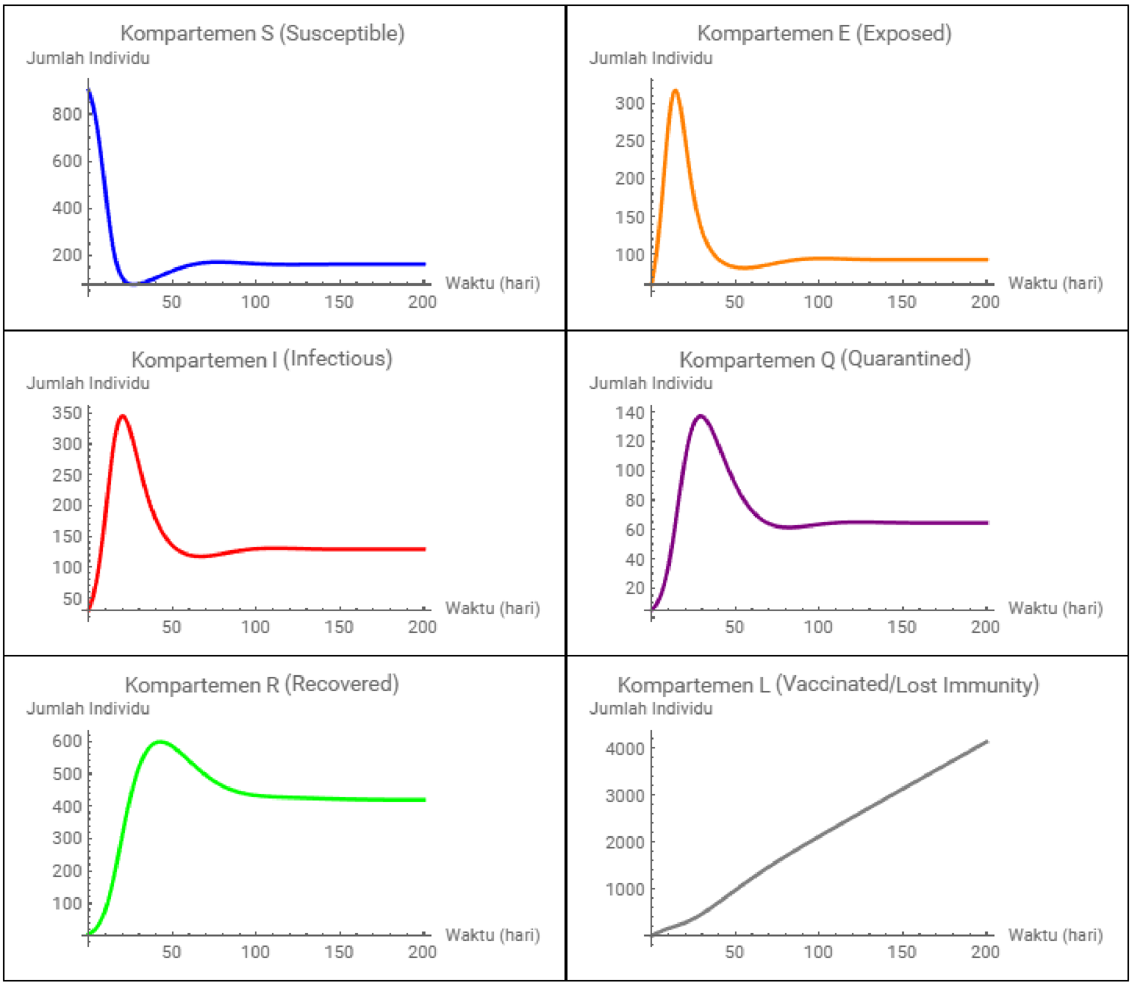

Figure 2. Human population dynamics when $R_0 > 1$

The simulation results show that compartment S decreases as susceptible individuals move to compartment E through social and digital influences, and to compartment L through early literacy. Compartment E increases in the early phase, then decreases after some individuals move to compartment I. Compartment I serves as the primary risk indicator. In the early stages of the simulation, the number of individuals in Compartment I increases because the rate of exposure remains higher than the rates of recovery and quarantine. Once recovery interventions and regulations take effect, the number of individuals in Compartment I begins to decline. Compartment L continues to grow because financial literacy functions as a cumulative terminal compartment.

3.6 Basic Simulation Results

The simulation results show that compartment S decreases as susceptible individuals move to compartment E through social and digital influences, and to compartment L through early literacy. Compartment E increases in the early phase, then decreases after some individuals move to compartment I.

Compartment I serves as the primary risk indicator because it identifies individuals who have engaged in risky online borrowing. In the early stages of the simulation, the number of individuals in Compartment I increases because the rate of exposure remains higher than the rates of recovery and quarantine. Once recovery interventions and regulations take effect, the number of individuals in Compartment I begins to decline. Compartment L continues to grow because financial literacy functions as a cumulative terminal compartment.

3.7 Analysis of Intervention Scenarios

The simulation continued with four scenarios to examine the impact of regulation and financial literacy on the number of individuals at risk. These scenarios were designed based on changes in the values of δ and v.

Tabel 3. Intervention Scenarios

Scenario	δ	v	Meaning
Base	0.05	0.02	Low regulation and literacy
Strong regulation	0.15	0.02	Increased oversight and restrictions
Strong literacy	0.05	0.08	Increased financial education
Regulation and literacy	0.15	0.08	Integrated policies

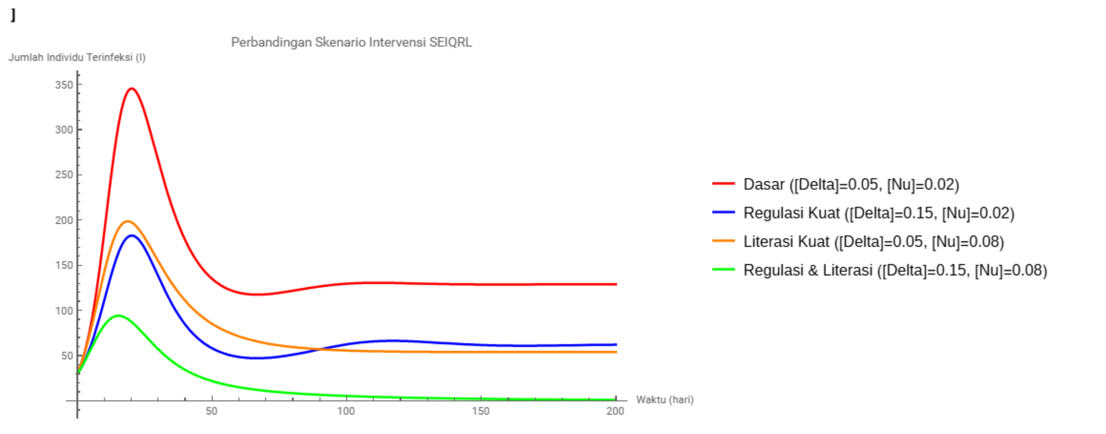

Figure 3. Intervention Scenarios from Wolfram Mathematica

The simulation results show that the baseline scenario results in the highest number of individuals at risk. In the strict regulation scenario, the number of individuals in

Compartment I declines more rapidly. An increase in the value of δ indicates that access restrictions, oversight of service providers, blocking of illegal services, and integration of risk data can reduce the duration during which individuals remain at risk.

In the strong literacy scenario, the number of at-risk individuals also decreases through a different mechanism. Financial literacy mitigates risk from the outset by shifting individuals from compartment S to L. The regulation and literacy scenario yields the largest reduction in I(t), indicating that a single policy is not sufficient to control online lending risk.

3.8 Comparison of Scenarios

The simulation results show that the baseline scenario results in the highest number of individuals at risk. In the strict regulation scenario, the number of individuals in Compartment I declines more rapidly. An increase in the value of δ indicates that access restrictions, oversight of service providers, blocking of illegal services, and integration of risk data can reduce the duration during which individuals remain at risk.

In the strong literacy scenario, the number of at-risk individuals also decreases through a different mechanism. Financial literacy mitigates risk from the outset by shifting individuals from compartment S to L. The regulation and literacy scenario yields the largest reduction in I(t), indicating that a single policy is not sufficient to control online lending risk.

3.9 Analysis of the R_0 Value in Each Scenario

The R_0 value is calculated using the formula:

$$R_0 = \frac{\beta \Lambda}{[\nu(\gamma + \delta)]}$$

]

Skenario	Nilai R0
Dasar	6.1538
Regulasi Kuat	3.4783
Literasi Kuat	1.5385
Regulasi dan Literasi	0.8696

Figure 4. Results of the R_0 Calculation from Wolfram Mathematica

Tabel 4. R_0 Values in Each Scenario

Scenario	R_0 Value	Interpretation
Base	6.1538	Strong spread risk
Strong regulation	3.4783	Risk is decreasing, but not yet under control
Strong literacy	1.5385	Risk is much lower
Regulations and financial literacy	0.8696	Risk is controllable ($R_0 < 1$)

The R_0 value in the baseline scenario is greater than one, meaning that risky online lending behavior can still spread within the population. The combination of regulation and financial literacy results in an R_0 value < 1, so the system moves toward a controlled state.

The results of the study indicate that the use of high-risk online loans can be understood as a process of behavioral diffusion within a population. These findings are consistent with the study by Ho, Shi, and Zhang (2024), which demonstrates the presence of peer effects in the peer-to-peer lending market. The SEIQRL model makes a conceptual contribution by adding two important compartments Q and L that do not appear explicitly in the basic SEIR model.

Mathematically, the R_0 formula shows that early literacy (v), recovery (γ), and regulatory quarantine (δ) all play a role in reducing the basic reproduction number. However, simulations indicate that literacy and regulation have different roles. Regulation reduces risk after an individual enters Group I, whereas literacy reduces risk before an individual enters the exposure pathway.

These findings are relevant to the situation in Indonesia. As of January 31, 2025, there were 97 LPBBTI operators licensed by the OJK, indicating that online lending services have become an important part of the national digital financial ecosystem. Hasan, Horvath, and Mares (2022) note that limited financial literacy is associated with widening wealth inequality, which is consistent with the model's finding that low literacy rates (v) elevate R_0. Moreover, the peer effects documented by Gao, Zhu, and Ma (2024) in online credit markets align with the model's β parameter, which captures social and digital influence driving individuals from S to E. These convergences across independent studies strengthen the empirical plausibility of the SEIQRL model's behavioral assumptions.

Theoretical Implications. This study contributes to the mathematical modeling literature by demonstrating that the epidemiological framework can be extended beyond biological contexts to capture behavioral financial risk dynamics. The SEIQRL model expands the classical SEIR structure (van den Driessche & Watmough, 2002) by incorporating regulatory quarantine and financial literacy as distinct intervention pathways. Theoretically, this formulation shows that R_0 is a function of both preventive (v) and curative (δ) parameters simultaneously, which implies that neither regulatory enforcement alone nor financial education alone can achieve effective risk control. The model thus provides a mathematical justification for integrated dual-intervention strategies, extending the findings of Zhao et al. (2021) by operationalizing regulatory and literacy mechanisms within the compartmental structure itself.

Practical Implications. From a policy perspective, the simulation results provide actionable guidance for Indonesian financial regulators and educational institutions. First, the OJK should prioritize an integrated approach combining platform-level regulation (increasing δ) with community-based financial literacy programs (increasing v), rather than relying exclusively on reactive enforcement. Second, early financial literacy specifically targeting individuals who have not yet taken out online loans (S→L) has a larger structural impact on R_0 than post-infection regulatory quarantine, because it removes individuals from the risk pathway entirely. This finding aligns with the 2024 National Survey on Financial Literacy and Inclusion (OJK & BPS, 2024), which revealed a persistent gap between financial inclusion (75.02%) and financial literacy (65.43%), indicating that literacy interventions remain critically underdeveloped relative to access expansion. Third, for institutions such as universities and schools, the Literate (L) compartment suggests that financial education curricula should be designed as permanent behavioral outcomes, not one-time exposures. The SEIQRL framework can serve as an evaluation tool to model the population-level effects of proposed literacy programs before implementation.

4. CONCLUSION

This study develops the SEIQRL model to analyze the dynamics of risky online loan usage in Indonesia. The results of the analysis show that the risk-free point occurs when the E, I, and Q compartments have a value of zero. Numerical simulation results using Wolfram Mathematica show that the regulation and literacy scenarios yield the most effective outcomes. The baseline scenario yields $R_0 = 6.1538$, while the combined scenario yields $R_0 = 0.8696$. Controlling high-risk online loans cannot be adequately achieved through blocking or restricting access; financial literacy must be prioritized as the primary strategy to prevent the public from falling into harmful patterns of online loan usage.

5. ACKNOWLEDGMENTS

The author extends his deepest gratitude to the Faculty of Mathematics, Natural Sciences, and Earth Sciences (FMIPAK) at the State University of Manado for the permission, facilities, and data access provided during the observation and data collection process for this research. The author also extends high appreciation to the supervising lecturers and colleagues in the Department of Mathematics Education who have provided critical input, methodological guidance, and invaluable technical support in refining this

operations research model. May the intellectual contributions in this article yield tangible impacts on the development of campus facilities and infrastructure.

6. RECOMMENDATIONS

Future research could further develop this model by utilizing empirical data from the OJK, BPS, or digital financial institutions. Model parameters could also be estimated using real-world data to ensure more accurate simulation results. Additionally, future studies could incorporate factors such as income, age, education level, employment status, and social media usage intensity as variables influencing the dynamics of online loan risk.

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