Roll Rate-Based Expected Credit Loss Analytics for Sustainable Trade Receivables Governance in a Non-Financial Firm

Titis Wahyuni[1]* and Adief Ghifari Syahviar[2]

[1] Vocational Education Program, Universitas Indonesia, Depok, Indonesia
[2] Vocational Education Program, Universitas Indonesia, Depok, Indonesia
t.wahyuni@ui.ac.id, adief2015@gmail.com

Abstract. This study evaluates the application of the roll rate method for measuring ex-pected credit loss (ECL) on trade receivables and examines its role in support-ing sustainable trade receivables governance in a non-financial firm. A descrip-tive case study approach was used based on anonymized secondary case doc-umentation from PT A. The analysis examined a 36-month aging schedule, re-ceivables migration across aging buckets, probability of default (PD), loss giv-en default (LGD), exposure at default (EAD), forward-looking adjustment, and final ECL/allowance calculation. The findings show that roll rate-based ECL analytics can transform static aging schedule data into dynamic credit risk in-formation. In the case analyzed, the final probability-weighted ECL was Rp83,455,523, or approximately 1.58% of total trade receivables. The results also show that receivables in the 1–30 days bucket produced the largest ECL contribution due to high exposure, while older aging buckets showed higher risk intensity. The study demonstrates that the roll rate method supports credit risk monitoring, impairment estimation, internal control, data traceability, and cash flow planning. However, the reliability of the method depends on data quality, consistency of aging classification, adequacy of historical observa-tions, reasonableness of PD and LGD assumptions, and model validation. This study contributes to accounting analytics and ECL literature by showing how trade receivables data in non-financial firms can be transformed into decision-useful credit risk information for sustainable receivables governance.

Keywords: expected credit loss, roll rate method, trade receivables, credit risk analytics, sustainable receivables governance Third Keyword.

1 Introduction

Trade receivable is a critical component of current assets in non-financial firms be-cause it is closely related to revenue recognition, trade credit policies, liquidity, work-ing capital, and firm performance. Credit sales can maintain customer relationships and support sales growth, but they also pose the risk of delayed or failed payments, which may affect cash flow, collection costs, and operational risk [1], [2], [3], [4].

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Delays in receivables collections increase cash flow uncertainty, limit financial flexibility, and may weaken a firm's access to financing. Late in payments may also lead to credit restrictions and less favorable financing terms. Therefore, Trade receivable management should be positioned as part of a company's credit risk management, working capital resilience, and financial sustainability [4]. The risk of uncollectibility also affects financial reporting because inaccurate allowance estimates may cause assets and earnings to be overstated and reduce the reliability of accounting information. Timely loss recognition, effective internal controls, and auditors' attention to trade credit risk are associated with improved accounting information quality [5], [6], [7].

The expected credit loss (ECL) model requires companies to estimate future credit losses without waiting for evidence that a loss has occurred. This approach transforms the reactive incurred loss model into a forward-looking, probability-weighted measurement. ECL estimates should consider reasonable and supportable information, a range of possible outcomes, changes in economic conditions, and the probability of default over the life of the financial asset [5],[8],[9].

In the context of trade receivables, impairment measurement cannot rely solely on the aging schedule at the end of the period because the report only provides a point-in-time view. Portfolios with the same aging composition may have different risk levels when historical migration patterns, collection performance, and the likelihood of progressing to default are considered. Therefore, ECL measurement requires reliable historical data, consistent aging bucket definitions, and a method capable of tracing changes in credit quality across periods [9], [10].

The roll rate method addresses these needs by tracing the movement of receivables balances from current to overdue and default categories. Estimated expected credit losses (ECL) are calculated by combining the estimated probability of default (PD) by utilizing the trend of shifting receivables balances with losses if default (LGD) and the value of receivables exposure at the time of default (EAD). With this method, accounting data is transformed into information to predict customer payment behavior, monitor credit risks and maintain smooth cash flow. This is in accordance with the concept of analytical accounting [11], [12]. In this condition, the aging schedule becomes an increasingly important source of information that shows the development of receivables quality.

In order for ECL estimates using the roll rate method to be reliable, companies need to use complete historical data, consistent age classification of receivables, proper reconciliation of receivable balances, use sufficient observation periods, and have all adequate assumptions properly documented. ECL estimation results can be less accurate if customers are not properly identified, credit terms change, payment history is incomplete, and data governance is poor. Thus, roll rate implementation not only requires good data governance, but must be supported by a reliable information system, effective internal control, the use of professional judgment, and monitoring from management.

Sustainable trade receivables governance in this study is defined as a company's capability to manage receivables effectively so that financial condition and cash flow are maintained, accounts receivable impairment calculations are carried out accurately, and the risk of customer default can be handled and accounted for properly. To produce

accurate ECL estimates, detect deterioration in receivables quality early, determine receivables that should be collected first, and support the continuity of company operations, companies must have quality data, reliable information systems, and adequate internal controls. Thus, effective receivables management helps maintain liquidity and strengthen company resilience, while the quality of information systems and internal control strengthens accounting information and decision-making [13], [14].

However, the use of receivables data as the analytical basis for ECL in non-financial firms remains suboptimal and is often influenced by the delinquency status at a single reporting date. Roll rates method can address these limitations, but their application requires consistent age classification, an adequate observation horizon, appropriate treatment of recoveries and write-offs, and transparent assumptions. Historical results must also be adjusted if forward-looking information indicates changes in future collection conditions [11], [14].

This research gap arises because the ECL literature is still dominated by the banking context, particularly regarding staged provisioning, probability of default modeling, and credit portfolio risk. However, the data, regulatory, and credit portfolio characteristics of banks differ from those of non-financial companies' accounts receivables [5], [8], [9], [15]. Research on non-financial companies has focused more on the general impact of IFRS 9 on allowances for doubtful accounts, trade receivables, liquidity, and cash holdings [16]. Research specifically explaining the transformation of historical aging data through roll rates into PD, LGD, EAD, and ECL is still limited. Furthermore, few studies have utilized roll rate-based ECL analytics as an integrated instrument for impairment measurement, credit risk monitoring, internal control, data traceability, and cash flow resilience.

This study fills this gap by applying the roll rate method to 36 months of accounts receivable aging data at a non-financial company. The movement pattern between aging buckets is used to estimate PD, then combined with LGD and EAD, and forward-looking adjustments, to calculate ECL. Thus, the roll rate is positioned not merely as a technique for calculating impairment losses, but as an accounting analytics approach to support sustainable accounts receivable governance.

Based on this background and gap, this study aims to answer three research questions: (i) how the roll rate method is applied to measure expected credit loss on accounts receivable in non-financial companies, (ii) how measuring expected credit loss based on the roll rate method can contribute to strengthening sustainable accounts receivable governance, and (iii) what are the practical advantages and limitations of the roll rate method in supporting data-based accounts receivable credit risk assessment?

This study aims to evaluate the application of the roll rate method in measuring accounts receivable (ECL) in non-financial companies. Specifically, this study examines the transformation of historical accounts receivable aging data into roll rates, PD, LGD, EAD, and ECL. It also explains the role of roll rate-based credit risk analytics in supporting impairment measurement, internal control, accounts receivable risk monitoring, collection prioritization, and cash flow resilience.

This study provides three main contributions. First, it expands the ECL and accounting analytics literature by focusing on accounts receivable in non-financial companies. Second, it provides empirical evidence regarding the transformation of a 36-

month aging schedule into a measurable credit risk indicator using the roll rate method. Third, this study offers a practical framework for accountants, auditors, finance managers, and credit function managers to use accounts receivable data in impairment measurement, internal control, collection monitoring, cash flow management, and sustainable accounts receivable governance. With this integration, the aging schedule can evolve from a static reporting instrument into a data-driven mechanism for credit risk assessment and strengthening financial resilience.

2 Literature Review

2.1 Trade Receivables and Credit Risk in Non-Financial Firms

Trade receivables represent a company's claim against customers arising from the sale of goods or services on credit. In non-financial firms, receivables are an important component of working capital because they are directly related to the cash conversion cycle, liquidity, and firm performance. Therefore, receivables management is not merely administrative, but also strategic in maintaining the continuity of the firm's operations [1],[17].

However, receivables also contain credit risk because cash realization depends on customers' ability to pay. This risk may affect the required allowance, asset quality, and the firm's liquidity position [13],[16]. Thus, receivables should be understood as current assets that simultaneously contain credit risk exposure and require reliable impairment measurement.

2.2 Expected Credit Loss on Trade Receivables

Expected credit loss (ECL) is an impairment measurement approach that estimates credit losses expected to occur in the future. Unlike the incurred loss model, ECL does not wait for objective evidence of loss, but considers historical experience, current conditions, and forward-looking information. In the context of trade receivables, IFRS 9 provides a simplified approach that requires the recognition of lifetime expected credit losses from initial recognition [5],[18], [19].

Conceptually, ECL consists of three main components: probability of default (PD), loss given default (LGD), and exposure at default (EAD). Reliable ECL estimation requires historical portfolio data, exposure characteristics, and adjustments for economic conditions and future expectations [8],[20],[21]. The IFRS 9 literature also emphasizes the need for dynamic default risk modelling over the life of the exposure, including approaches that capture changes in PD over time [9].

2.3 The Roll Rate Method as Credit Risk Analytics

The roll rate method is an analytical technique used to trace the movement of receivable balances across aging buckets from one period to the next. Movement from current categories to increasingly overdue categories indicates a deterioration in credit quality,

while movement back to less delinquent categories indicates improvement or a cure movement. This logic is consistent with the transition matrix approach in the credit risk literature, which is used to capture the dynamic migration of exposures across risk states [22].

In ECL measurement, migration patterns across aging buckets can be used as the basis for estimating PD because payment delinquency indicators, or days past due, represent debtor credit deterioration [23]. Compared with an aging schedule that only presents the receivables position at a single date, the roll rate method provides more dynamic information on changes in receivables quality over time. Thus, the roll rate method bridges historical receivables aging data with the need for more predictive ECL measurement [22],[24].

2.4 Digital Accounting Analytics and Receivables Governance

Digital accounting analytics refers to the use of accounting data and analytical techniques to support reporting, control, risk management, and decision-making. In receivables management, data on customer balances, invoice dates, due dates, payment history, aging schedules, and collection activities can be transformed into risk information. Thus, the accounting function evolves from transaction recording into a provider of data-driven information for management [25], [26].

ECL measurement using the roll rate method is a form of financial analytics because it uses historical data to estimate the migration of receivables toward default. This approach is consistent with IFRS 9, which requires ECL estimates to be based on historical information, current conditions, and forward-looking information [27], [28], [29], [30].

For analytical results to be reliable, receivables governance must be supported by data quality and internal control. Errors in aging classification, incomplete payment data, weak credit limits, or undocumented assumptions may reduce the reliability of ECL estimates. Therefore, receivables governance requires data validation, segregation of duties, credit authorization, balance reconciliation, methodological documentation, and adequate audit trails [31], [32], [33], [34].

2.5 Sustainable Trade Receivables Governance

In this study, sustainable trade receivables governance refers to receivables governance that maintains asset quality, liquidity, and cash flows on a sustainable basis through credit risk control and working capital management. The concept of sustainability is not interpreted as environmental sustainability, but as financial sustainability, cash flow resilience, working capital sustainability, receivables quality, and the reliability of impairment estimation [35], [36].

Receivables quality needs to be monitored because a decline in customers' payment ability may increase cash requirements, reduce firm value, and put pressure on profitability. The trade credit literature shows that excessive credit granting or long collection periods can increase risk and reduce sustainable profitability [37], [38].

In this context, roll rate-based ECL analytics functions as a mechanism that connects receivables data, credit risk estimation, and cash flow resilience. This analysis helps firms identify patterns of deterioration in receivables quality, estimate default risk, and adjust credit and collection strategies. Its reliability still depends on adequate validation, authorization, reconciliation, documentation, and monitoring [39], [40], [41], [42]. Thus, sustainable trade receivables governance integrates working capital management, accounting analytics, internal control, and ECL measurement to maintain receivables quality and the firm's financial sustainability.

2.6 Conceptual Framework

Based on the preceding description, the conceptual framework of this study is built on the understanding that sustainable trade receivables governance cannot be supported solely by the recording of receivables balances or by a static aging schedule. Sustainable receivables governance requires risk information that is more dynamic, traceable, and relevant for decision-making.

In this study, trade receivables data serve as the primary input and are first classified into an aging schedule. The data are then analyzed using the roll rate method to identify the movement of receivables across aging buckets. The movement from one receivables aging bucket to another is used to estimate the probability of default (PD). This PD value is then combined with the loss in case of default (LGD) and the exposure value of receivables at the time of default (EAD) to obtain an estimated expected credit loss (ECL).

The ECL value is used not only to calculate allowances for impairment losses but also to provide companies with information they can use to monitor receivables quality, assess customer risk, and plan cash flow. Accurate ECL analysis requires well-documented data, consistent aging of receivables, and effective internal controls. Therefore, the ECL using the roll rate method helps companies link receivables impairment, receivables monitoring, and ongoing receivables management.

3 Methods

This research uses a descriptive case study approach with a case-based analytical study design. This approach was selected because the research aims to analyze the application of roll rate-based expected credit loss analytics to trade receivables in a non-financial firm and to explain its contribution to sustainable trade receivables governance. The research does not aim to test causal relationships or produce statistical generalization, but rather to demonstrate how trade receivables data can be processed into credit risk indicators, ECL/ECL estimates, and data-driven receivables governance information.

The object of the research is the trade receivables of PT A, a non-financial firm that engages in credit sales transactions and has exposure to receivables risk. The company's identity is anonymized to maintain data confidentiality. This case was selected because the available documentation contains data that are relevant and adequate for analysis, including a 36-month trade receivables aging schedule, receivables balance at

the reporting date, aging bucket classification, roll rate calculation, probability of default (PD) estimation, loss given default (LGD), exposure at default (EAD), forward-looking adjustment, final ECL/allowance, and supporting evidence in the form of vouching, recalculation, and aging schedule analysis.

This study is based on available secondary case documentation from an applied accounting project at PT A; therefore, the collection of new primary data, direct observation of the company's information system, and interviews with management or auditors are outside the scope of the study. To maintain data confidentiality, individual customer information, invoice details, and monthly transaction data are presented in a limited form. Accordingly, this article focuses on aggregated data by aging bucket, summary roll rates, ECL parameters, and the results of the ECL allowance calculation.

Table 1. Data Components Used in the Analysis.

Data Component	Description	Function in the Analysis
Trade receivables data	PT A's trade receivables balance at the reporting date	Main object of ECL measurement
Historical aging schedule	Monthly receivables aging data over 36 months	Basis for roll rate analysis
Aging bucket	Classification of receivables based on days past due	Credit risk segmentation
Flow rate / roll rate	Rate of receivables movement across aging buckets	Measurement of receivables migration
Probability of default	Estimate of the likelihood of default based on aging migration	Default risk parameter
Loss given default	Estimate of the loss rate if default occurs	Loss severity parameter
Exposure at default	Receivables balance exposed to default risk	Credit exposure parameter
Forward-looking adjustment	Adjustment based on future economic information	Future risk adjustment
Vouching and recalculation documentation	Bukti penelusuran data dan pengujian ulang perhitungan	Dasar keterlacakan dan keandalan analisis

Table 1 summarizes the main data components used in the analysis and explains the function of each component in the roll rate-based ECL measurement process. The trade receivables balance and historical aging schedule serve as the primary input data for identifying receivables exposure and aging patterns. Aging buckets and roll rates are used to classify credit risk and capture the movement of receivable balances across delinquency categories. The ECL parameters, consisting of PD, LGD, and EAD, are then used to estimate expected credit losses, while the forward-looking adjustment incorporates future economic considerations into the measurement. In addition, vouching and recalculation documentation are used to support the traceability and reliability of

the analysis. Therefore, Table 1 provides the methodological link between the available case documentation, the ECL calculation process, and the governance interpretation developed in this study.

Data analysis was conducted through document-based content analysis and case-based analytical reconstruction. Content analysis was used to identify, classify, and interpret information contained in the case documents. The analytical categories included receivables input data, aging bucket classification, receivables migration patterns, credit risk parameters, forward-looking adjustment, ECL allowance output, evidence of data traceability, and implications for receivables governance. Subsequently, case-based analytical reconstruction was used to reconstruct the ECL calculation process from the perspective of roll rate analytics and governance.

The analysis was carried out by reviewing the 36-month historical aging schedule, identifying movements in receivable balances across aging buckets, calculating roll rates, estimating PD, examining LGD and EAD, and calculating the ECL allowance by considering forward-looking adjustment.

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The analysis was carried out by reviewing the 36-month historical aging schedule, identifying receivables balance transfers between aging buckets, calculating the roll rate, estimating PD, reviewing LGD and EAD, and calculating the ECL allowance by considering forward-looking adjustments into account.

The main formula used was:.

$$Roll\ Rate = \frac{Receivables\ balance\ in\ the\ next\ aging\ bucket}{Receivables\ balance\ in\ the\ previous\ aging\ bucket} \quad (1)$$

$$ECL = PD \times LGD \times EAD \quad (2)$$

The reliability of the analysis was maintained by tracing the relationships among aging data, roll rate, PD, LGD, EAD, forward-looking adjustment, and the final ECL allowance. Vouching documentation was used to assess the traceability of aging data to supporting documents, while recalculation documentation was used to assess the mathematical accuracy of the ECL calculation. This study does not use evaluative scores, assessment weights, or indices whose basis for formation is not explained.

These analytical procedures were used to answer the three research questions. RQ1 was addressed by reconstructing the ECL calculation process, starting from the aging schedule, roll rate, PD, LGD, EAD, forward-looking adjustment, to the final ECL/CKPN. RQ2 was addressed by interpreting the ECL analytics results in terms of receivables risk monitoring, data traceability, internal control, and cash flow resilience. RQ3 was addressed by evaluating the practical advantages and limitations of the roll

rate method based on data quality, consistency of aging classification, adequacy of historical data, reasonableness of assumptions, and the need for model validation.

The methodological limitations of this research lie in the use of a single case study, secondary data, and aggregate aging data. Therefore, the results are not intended for statistical generalization and cannot trace receivables migration at the invoice or individual customer level. Although the data presented is aggregate data, the ECL parameters and calculation results used can be understood by the reader.

4 Result and Discussions

4.1 Result

The results of PT A's ECL calculation using the roll rate are as follows. The calculation was performed using 36 months of receivables aging data, from January 2023 to December 2025, and the receivables balance at the financial reporting date. The data is used to observe the movement of receivables across aging buckets, calculate the percentage of receivables transfer, and calculate the probability of receivables defaulting (PD). The results of this calculation are used to calculate the estimated expected credit loss (ECL).

PT A's total receivables at the financial reporting date before being reduced by the ECL reserve were IDR 5,276,041,223. The distribution of exposure at default (EAD), ECL after scenario weighting, and the contribution of each aging bucket to the total ECL are presented in Table 2.

Table 2. Trade Receivables Profile and ECL Contribution

Aging Bucket	EAD (Rp)	EAD Proportion
Not yet due	730,637,758	13.85%
1–30 days	4,453,865,754	84.42%
31–60 days	78,916,960	1.50%
61–90 days	12,340,901	0.23%
91–120 days	83,850	0.00%
More than 120 days	196,000	0.00%
Total	**5,276,041,223**	**100.00%**

Source: Case data processed by the author.

Table 2 shows that the 1–30-day group has the largest balance, at IDR 4,453,865,754, or 84.42% of total receivables. This bucket also contributes the largest ECL, at IDR 52,206,217, or 62.56% of total ECL. Conversely, receivables past 30 days only account for 1.73% of the total balance but contribute 28.06% of total ECL. These results indicate that ECL is influenced by two factors: the magnitude of exposure and the level of risk in each aging bucket.The roll rate was used to measure the transfer of balances from one aging bucket to the next.

The formula used is as follows:

$$Roll\ Rate_{i,t} = \frac{Receivables\ balance\ in\ the\ next\ aging\ bucket\ at\ month\ t}{Receivables\ balance\ in\ the\ originating\ aging\ bucket\ at\ month\ t-1}$$

The average roll rate over the 36-month period was then used to calculate the cumulative probability of default (PD). The results of the roll rate and cumulative PD calculations are presented in Table 3.

Table 3. Average Roll Rate and Cumulative PD

Aging Bucket Transition	Average Roll Rate	Cumulative PD
Not yet due to 1–30 days	91.43%	0.48%
1–30 to 31–60 days	5.51%	0.52%
31–60 to 61–90 days	41.48%	9.46%
61–90 to 91–120 days	50.18%	22.80%
91–120 to more than 120 days	45.44%	45.44%
More than 120 days to default	100.00%	100.00%

Source: Processed 36-month aging schedule.

Table 3 shows an increase in risk after receivables pass 30 days overdue. The roll rate from the 1–30 days bucket to the 31–60 days bucket was 5.51%, then increased to 41.48% in the transition from the 31–60 days bucket to the 61–90 days bucket. Cumulative PD also increased from 0.52% to 9.46%. After receivables passed 60 days overdue, the roll rate reached 50.18% and cumulative PD increased to 22.80%. These results indicate that the 30-day and 60-day thresholds are important points for identifying deterioration in receivables quality.

The roll rate of 91.43% from the not-yet-due bucket to the 1–30 days bucket should be interpreted carefully. This value was calculated based on aggregated aging schedule balances, rather than by tracking the same invoices from month to month. Therefore, the figure may be affected by newly due invoices, customer payments, credit notes, reclassifications, or changes in credit sales volume. Thus, the roll rate in this study represents a migration estimate based on aggregated data.

ECL is obtained from the calculation results that combine PD, LGD, and EAD which is shown by the following formula:

$$ECL=PD\times LGD\times EAD$$

PT A's receivables that are more than 120 days past due are considered a default exposure. Based on the calculation, the LGD value is 100.27% because the present value of the receivables collection proceeds is negative. Therefore, the LGD value needs to be

carefully defined, specifically by matching the amount of receivables in default with the cash from collections based on data for each invoice or customer.

The ECL value is calculated using three economic scenarios: a base scenario, an optimistic (upside) scenario, and a pessimistic (downside) scenario. The calculation results can be seen in Table 4 below.

Table 4. ECL Based on Economic Scenarios

Scenario	Inflation Assumption	ECL Before Weighting (Rp)	Weight	Weighted ECL (Rp)
Base	2.56%	83,315,898	60%	49,989,539
Upside	2.46%	84,712,155	25%	21,178,039
Downside	2.66%	81,919,640	15%	12,287,946
Final probability-weighted ECL			**100%**	**83,455,523**

Source: Processed case data.

Based on the results presented in Table 4, PT A's final ECL value is Rp83,455,523, or approximately 1.58% of the total receivables obtained through the weighting of three economic scenarios. For the baseline scenario, the weighting is 60%. The optimistic (upside) scenario has a weighting of 25%, and the pessimistic (downside) scenario has a weighting of 15%. The ECL generated by the optimistic (upside) scenario is greater than the ECL generated by the pessimistic (downside) scenario. However, the upside scenario produced a higher ECL than the downside scenario. This pattern indicates that the relationship between the inflation assumption and default risk in the model is not yet fully consistent; therefore, the scenario definitions, weighting basis, and forward-looking adjustment mechanism still need to be calibrated and retested.

Overall, the findings show that the 36-month aging schedule data can be processed into roll rates, cumulative PD, and scenario-weighted ECL. These results indicate that the roll rate method can be applied to measure ECL on trade receivables in a non-financial firm, although the results should still be interpreted with consideration of data quality and the reasonableness of model assumptions.

4.2 Discussion

The findings show that the roll rate method can transform a static aging schedule into more dynamic credit risk information. Aging schedules typically only show the position of receivables based on the age of the receivables as of a specific date. Through the roll rate, this data can be used to understand how receivables balances move from lower-risk buckets to higher-risk buckets. Thus, the roll rate provides more predictive information than the merely descriptive aging schedule.

Findings at PT A indicate that the largest ECL value is generated by the group of receivables that are due within 1-30 days. This is because this group has the largest amount of receivables. On the other hand, groups of receivables that have longer re-

ceivables have smaller balances but have a higher risk of default. These findings indicate that with the roll rate method it can be identified whether the ECL value (source of risk) comes from the large balance of receivables or the increased risk of default.

From the perspective of ECL measurement, the research findings confirm that the ECL value is determined not only by the amount of the receivables balance, but also by the combination of PD, LGD, and EAD. The 1–30-day bucket generates the largest ECL due to the group had the largest outstanding balance, while older buckets have a higher probability of default despite their smaller balances. Therefore, the roll rate method helps firms distinguish between risks stemming from balance concentration and risks arising from an increased probability of default.

The results of this analysis indicate that the roll rate method can be used as an analytical accounting tool. The accounting function plays a role not only in recording transactions but also in providing information for decision-making. In this study, accounting data, in the form of accounts receivable, is used not only to prepare financial statements but also to process information to support risk monitoring, estimating customer credit losses, collection policies, and cash planning.

In sustainable accounts receivable governance, ECL analysis not only functions to determine impairment losses on receivables but also to assist companies in managing their accounts receivable properly. All calculations can be traced well, starting from grouping receivables aging, calculating roll rates, the possibility of customer default (PD), the amount of loss at the time of default (LGD), and the value of receivables at the time of default (EAD), adjustments based on information/estimates of future economic conditions (forward looking), to generate ECL values. Information on the resulting ECL value is not only used to record transactions but also to manage receivables and maintain the company's financial sustainability. The management of receivables in question includes monitoring the quality of receivables, assessing customers who have risks, determining the priority collection order and supporting sustainable cash flow.

Meanwhile, the results of this study also indicate that the use of roll rates requires caution because the aggregate value used does not reflect the movement of receivables from the same invoices or customers between periods. Furthermore, this study also found that LGD exceeded 100%, PD values above the logical limit for certain aging bucket, and upside scenarios resulted in higher ECL than downside scenarios. This confirms the limitations of the model. The reliability of calculations using the roll rate method is determined by the quality of the data used, the consistency of the receivables aging grouping, the recording of basic assumptions, and the results of comparing the ECL values estimated using the model with the actual results of receivables collection and payments made by customers in the following period.

Thus, the primary contribution of this research lies not only in calculating ECL, but also in mapping the relationships between receivables aging data, risk migration, ECL parameters, internal controls, receivables monitoring, and cash flow resilience. This mapping demonstrates that roll rate-based ECL analytics can be both an impairment measurement tool and a data-driven receivables governance instrument.

5 Limitations

This study has several limitations. First, it used a single case study at PT A, therefore, the findings are not intended for statistical generalization. Second, the data used comes from secondary case documentation and were based on an aggregate aging schedule, so the analysis cannot trace receivables transfers at the invoice or individual customer level. Consequently, changes in balances between aging buckets may be influenced by new invoices, payments, credit memos, reclassifications, or changes in credit sales volume. Third, this study did not involve interviews with management, accountants, auditors, or modelers, so managerial considerations and the judgmental basis for the model's assumptions cannot be directly confirmed. Furthermore, several model outputs, such as LGD above 100%, PD exceeding the logical limit in certain buckets, and ECL in the upside scenario being higher than the downside, indicate that the model still requires calibration, validation, and backtesting.

6 Conclusion

This study demonstrates that the roll rate method can be applied to measure expected credit loss (ECL allowance) on accounts receivable in non-financial companies. In the case of PT A, this method uses a 36-month aging schedule, receivables movement patterns between aging buckets, PD, LGD, EAD estimates, and forward-looking adjustments to produce a final ECL of IDR 83,455,523, or approximately 1.58% of total accounts receivable.

The results of this study indicate that the roll rate method can be used to generate expected credit losses (ECL) and evaluate changes in credit risk. Integrating the aging schedule as a historical data source with the roll rate used to evaluate receivables migration, and the PD, LGD, and EAD parameters used to measure credit risk, will result in transparent and traceable ECL estimates.

This study also confirms that ECL serves not only as the basis for recognizing credit loss allowance but also as governance information to assist in producing reliable reporting and ensuring sound cash flow management. ECL estimation using the roll rate method also supports the formation of loss reserves, supports companies in managing receivables through monitoring receivable quality, assessing risky customers, strengthening internal controls, and assisting in cash flow planning.

7 Recommendations For Further Research

Future research may use multiple case studies in non-financial companies from different industries to compare roll rate patterns, PD estimates, LGD assumptions, and ECL results across contexts. It is also recommended that future research use invoice-level or customer-level data to more accurately track receivables migration.

Furthermore, future research could involve interviews with accountants, auditors, management, and modelers to understand the judgments and assumptions used in ECL

measurements. Future research could also compare the roll rate method with the provision matrix, develop an accounting analytics dashboard for receivables monitoring, and conduct backtesting between ECL estimates and actual collections..

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