Contributions on Automating the Financial Dunning Process Using Machine Learning

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Abstract
Dunning refers to the process of methodically pursuing payment of a debt. The practice of dunning has been around for centuries, but technological developments, especially in Machine Learning (ML), present a chance to automate and optimize important processes, increasing recovery rates and improving customer satisfaction. The research's objectives were to learn more about the difficulties arising from the dunning process's lack of automation through machine learning (ML) and to create a solution that effectively automates the financial process by incorporating ML. To determine the primary obstacles, inefficiencies, and places in the dunning process that are best suited for automation, this article first offers a survey and a review of the literature. It provides a better grasp of how businesses currently manage dunning and the issues that impede productivity by examining industry data and professional viewpoints. The paper expands on these discoveries by offering a specific machine learning-driven automation solution intended to optimize the dunning procedure. By using predictive analytics to improve client segmentation, optimize communication scheduling, and predict payment patterns, this strategy eventually improves operational effectiveness and financial results. The essay illustrates how intelligent automation may make the dunning process a more efficient and data-driven function by bridging the gap between theory and reality.

Keywords: Dunning; Financial Processes; Machine Learning; Automation; Accounts Receivables

Introduction

Companies in areas like telecommunications, electricity, utilities, and similar ones frequently face difficulties collecting payments from customers, which causes them to procrastinate in meeting their supplier responsibilities. According to research by (Meenal, 21 Jan 2025), a significant percentage of invoices from small and medium-sized businesses (SMEs) in the US and the UK are paid beyond the due date, with roughly 42.5% and 46% of invoices being paid after the due date, respectively. In the United Kingdom alone, this has resulted in an estimated £212 billion in unpaid debts; firms in Asia are facing comparable difficulties. Due to the significant effect that late payments can have on SMEs' capacity to efficiently manage financial flows, this issue is especially important to them.

Businesses use proactive strategies to solve issues in the invoice-to-cash cycle by communicating with clients to encourage and speed up on-time payments. Customers are informed, for instance, when a payment deadline is missed by means of electronic reminders sent by email or text message, or by direct phone contact started by a company person. The problem may worsen if the client doesn't respond to requests for payment, in which case the business may take more drastic actions like sending out more forceful communications, stopping services, or filing a lawsuit. This procedure, known in the literature as the Dunning process, entails a systematic and

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accelerated approach to client engagement with the goal of reducing the time required for debt collection.

For businesses to be financially stable, dunning is essential. An organization's liquidity can be significantly impacted by late payments, which can result in operational disruptions, a decrease in investment capacity, and an increase in financial risk. Through organized and transparent communication, effective dunning techniques assist companies in collecting past-due bills while maintaining client relationships.

New possibilities for dunning optimization are brought about by recent advancements in machine learning (ML) and artificial intelligence (AI). Businesses can adjust their dunning tactics by using machine learning (ML) algorithms to forecast which clients are most likely to make late payments based on past payment patterns. Machine learning (ML)-driven dunning solutions can increase recovery rates while decreasing manual labor and improving the customer experience by utilizing predictive analytics, intelligent customer segmentation, and automated communication optimization (Maryam Roshanaei) (Issam El Naqa, 2015).

The aim of the research was to gather information on the challenges caused by the lack of automation using Machine Learning in the dunning process and to develop a solution that addresses these issues by integrating ML to efficiently automate the financial process.

The article is structured into five main sections: Literature Review, Methodology, Results, Discussion, and Conclusion. The first section, Literature review, provides an outline of the dunning process, its present difficulties, and available technological solutions on the market nowadays, emphasizing how machine learning may improve automation of the dunning process.

In the second chapter, Methodology, the study presents the two research methods used by the authors: a survey to collect industry insights and a Proof of Concept (PoC) to confirm the viability of an ML-driven dunning solution. This section describes the design and implementation of the suggested automation framework, as well as the survey's structure, respondent selection, and data analysis methods.

The outcomes from the survey and the framework proposed are gathered in the Results section. The survey's findings underline the necessity for automation by exposing widespread inefficiencies in the dunning procedure. The PoC findings show how well ML algorithms optimize risk assessment, consumer segmentation, and tailored communication.

The last section, Conclusion, summarizes the study's findings, emphasizing the necessity of ML-driven automation of the financial dunning process. It also describes the possible development of using Machine Learning in financial dunning as well as future research areas.

Literature review

The financial dunning process is examined in this chapter along with its present tools, difficulties, and the automation role of machine learning. An introduction to the Dunning Process highlights its significance in the management of accounts receivable. Dunning Software and Tools Today, the next part, explores current technological solutions, emphasizing both their advantages and disadvantages. The chapter then discusses Dunning Process Challenges, pointing out inefficiencies such as manual labor, inadequate segmentation, and compliance hazards. Lastly, Machine Learning in the Dunning Process lays the foundation for the suggested ML-based solution by examining how AI-driven solutions may boost automation, forecast payment patterns, and increase efficiency.

The Dunning Process

Payment problems are unanticipated in the era of digital money, and one may not always be able to manage the cause. Transactions may be rejected for several reasons, such as insufficient cash, expired cards, or even problems with connection. Dunning is the practice of recovering lost income from denied credit cards and unsuccessful payments. (Suoniemi, 2018)

The term dunning was first used in the 17th century to describe the process in which a business owner communicates with one or more customers with the scope of collecting owed money for goods or services provided. (Bloomenthal, 2021) The term comes from "dun," an old English word that means to demand payment of a debt. (SAP S/4HANA Financial Accounting Certification Guide, 2021). Increasing levels of intensity are involved in this gathering process, which usually entails the following iterative steps:

- Making phone calls to customer to remind them of payments due;
- Sending formal letters to request the payment;
- In-person visits demanding payment;
- Third party collections agencies could be hired to rely on past-due clients;
- Threatening to take legal action;
- Executing litigation. (Bloomenthal, 2021)

There are different types of dunning that can be used, determined by variables including the amount of debt owing, client relationships, and the duration of past-due payments. Also, there may be a late payment penalty in addition to increasingly severe reminders. (SAP S/4HANA Financial Accounting Certification Guide, 2021) Although a company's accounts receivable department is often in charge of dunning, past-due payments may eventually be transferred to internal collections departments before being sent to outside collections firms. The majority of jurisdictions prohibit threats and intimidation. (Bloomenthal, 2021)

In other words, dunning refers to the process which starts if past due invoices are detected (Suoniemi, 2018). Payment failures may account for as much as 50% of lost revenue (Balcauski, 2021). Processing issues with the banks or payment provider produce a surprisingly high rate of customer attrition. Even though there are numerous reasons why payments could fail, many companies who deal with this issue manually might merely use simple retry logic (rerunning every Friday, for instance). To find the best solution for these technical payment processing problems, the businesses in this category use artificial intelligence (AI) and machine learning (ML) to analyze the problem throughout the payment system. (Balcauski, 2021)

Dunning Tools Nowadays

Traditionally, financial departments have handled the dunning process manually via phone calls, emails, and letters. Conventional approaches provide little flexibility or individuality and are based on preset timetables and templates. However, technological developments have resulted in the creation of automated dunning systems that are incorporated into CRM and ERP software. By automating reminders, monitoring payment statuses, and classifying clients according to risk profiles, these solutions expedite the procedure.

Nowadays, there are more and more tools that are either specifically designed for the dunning process or incorporate it. Modified dunning flows can be created with the majority of subscription management software. This gives businesses considerable flexibility in how they communicate and oversee the dunning process, but it takes internal knowledge to design the "best" procedure for your business and clients. Notably, subscription management systems frequently rely on corporate knowledge to direct the dunning process rather than industry best practices, and they typically do not address payment failure issues.

Table 1. Top Dunning Software Picks

Product name	Best of	Pricing	Product name	Best of	Pricing
Churnkey	Customer-obsessed teams	$$	Braintree	Small but complex small businesses	$$$
Stripe	Engineering-focused teams	$$	Churn Buster	E-commerce businesses	$$
Paddle	Entry-level solutions	$$$	Stunning	Entry-level, Stripe-only dunning	$$
Chargebee	Chargebee customer with basic needs	$$$	Butter Payments	Multinational corporations	$$$$

Reference: (Hall, The Best Dunning Software in 2024, 2024).

According to (Hall, The Best Dunning Software in 2024, 2024), the best dunning software in 2024 are presented in Table 1 along with the category in which they excel. However, all the 8-software described have the same disadvantage, shown in the last column - pricing. This is a key factor the authors of the paper addressed when creating the solution.

As 77% of the world's transaction revenue touches (Izabela Andreea Bostan, 2024) an SAP(R) system (SAP, 2020), one flexible software that already incorporates the dunning process is designed by SAP. By automating this process through SAP, businesses can streamline their collections management and improve cash flow. (Technologies, 2024) When business partners are delayed on payments, the SAP system's dunning feature offers extensive capabilities to address the situation. To reflect dunning duties, dunning groups, dunning levels, and dunning processes that align with your company model and industry norms, you can modify the SAP system. You may create dunning notices, manage agreed-upon non-payment periods, compute interest on outstanding items, and deliver them to business partners via fax, email, or mail. You can also handle business circumstances involving SAP systems in which the collections group has pursued the case as far as possible and future collection efforts necessitate the intervention of a collection agency or the legal department. (Manish, 2010)

Challenges in the Dunning Process

The financial dunning process presents a variety of challenges for businesses, even though it is essential for maintaining cash flow and lowering bad debt. These challenges range from operational inefficiencies to issues with the customer experience. Ineffective client segmentation leads to inefficient collection efforts, as businesses apply generic dunning strategies without considering customer risk profiles. Poor communication tactics and timing further complicate the process, as fixed reminder schedules do not align with customer behaviors, potentially damaging relationships (Meenal, 21 Jan 2025). High labor and operational costs arise from reliance on manual interventions, making the process slow and error-prone despite ERP integrations. Handling customer disputes is another obstacle, as unresolved invoice errors and unclear payment terms contribute to payment delays. Additionally, regulatory compliance with laws like GDPR and FDCPA is complex, requiring careful adherence to avoid legal and reputational risks (J. Behav., 2021). Lastly, lack of data analytics prevents businesses from predicting late payments proactively, resulting in inefficient, reactive strategies rather than optimized, data-driven collection efforts.

Machine Learning in the Dunning process

Machine learning algorithms' capacity to generalize to new jobs and learn from existing context might also enable advancements in the financial field, namely in the dunning process.

In order to capture the linear and nonlinear tendencies of financial variables, artificial intelligence applications are essential. (Shamima Ahmed, 2022) In particular, these applications enable us to resolve extremely nonlinear issues that are beyond the scope of conventional models. As a result, machine learning (ML) and deep learning techniques—a subset of artificial intelligence—have found extensive use in the banking industry. In the meantime, there has been a sharp increase in the body of research on the use of machine learning and deep learning. (Shamima Ahmed, 2022) (Bahrammirzaee, 2010) (J. Behav., 2021) (Wong, 1998) Therefore, the current study examines the literature on the critical roles that AI applications play in several financial domains, including big data analytics, anti-money laundering, stock price prediction, portfolio management, oil price prediction, bankruptcy prediction, and behavioral finance.

Machine Learning Algorithms

The core idea behind Machine Learning is the use of algorithms that can process large datasets, detect patterns, and make predictions or decisions. A machine learning algorithm is a sequence of processes or steps that an artificial intelligence system follows to accomplish tasks. (Le, 2024)

These algorithms are typically trained on historical data and then applied to new, unseen data to predict outcomes or classify information. For instance, financial organizations use different types of mathematical models to increase their profits and minimize their risks. Machine learning algorithms excel at analyzing vast datasets to identify patterns and predict future outcomes. (Business, 2025)

Another example is represented by the ML applications in credit market where ML algorithms can be used to appraise character and reputation variables when assessing future payment behavior. (Danika Wright, 2021)

Indeed, ML algorithms are tailored to different types of problems, such as classification, regression, clustering, and anomaly detection; therefore, they must be chosen based on their utility and the specific purpose of the AI application.

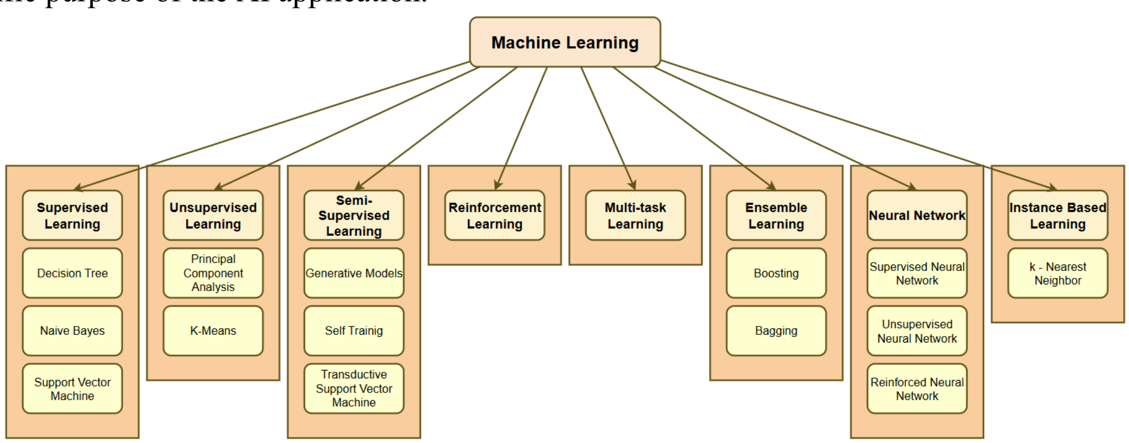

Figure 1. Machine Learning algorithms classification

Reference: Authors' own research.

According to Laurent Sindayigaya and Ayon Dey, in their review of ML algorithms we can clearly see a classification for all the existing algorithms. In this way, we can classify machine learning algorithms into four fundamental categories, depending on the nature of the data and the techniques used for model training. These categories are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. (Laurent Sindayigaya, 2022)

I. Supervised learning involves using a labeled dataset, where the target variables are already known. Algorithms trained on these data can make predictions or classify new data based on previous examples. This category includes both classification, which applies to problems where the target variable is discrete, and regression, which is used when the target variable is continuous. Examples of algorithms in this domain include logistic regression, support vector machines (SVM), decision trees, random forests, and neural networks. (Nasteski, 2017)

II. Unsupervised learning is applied to unlabeled datasets, where the algorithm must identify patterns or hidden structures within the data. This approach includes two important subcategories: clustering, which groups data based on common features, and association, which identifies relationships between variables. Algorithms used for these techniques include: K-Means, DBSCAN, and the Apriori and FP-Growth algorithms. (Samreen Naeem, 2023)

III. Semi-supervised learning combines both supervised and unsupervised learning, using both labeled and unlabeled data. This approach is useful in scenarios where fully labeling the data is costly or impossible. Semi-supervised learning algorithms, such as semi-supervised neural networks and label propagation methods, help improve model performance even when the dataset is partially labeled. (Jesper E. van Engelen, 2020)

IV. Reinforcement learning involves training an autonomous agent through interactions with an environment, where the agent receives rewards or penalties for its actions. Algorithms like Q-Learning, Deep Q Networks (DQN), and Actor-Critic methods are essential for developing intelligent agents that can make autonomous decisions based on feedback received. (Xinghui Zhu, 2024)

As a conclusion, each machine learning algorithm is tailored to specific data characteristics and objectives, such as performance, scalability, or interpretability. The choice of algorithm depends on the specific context, including data complexity, available resources, and the need for model explainability.

The research now takes a more focused and practical approach, building on the theoretical analysis that has been done thus far. In order to obtain industry insights, a survey was carried out to collect opinions from experts in a range of fields regarding the dunning process's current status, its difficulties, and potential automation opportunities through the use of machine learning (ML).

After that, the suggested IT solution will be presented as a workable and approachable Proof of Concept, showcasing its potential to improve the dunning process, considering these findings and the previously discussed notions.

Methodology

This study employs two main research tools: a demonstrative solution, to confirm the usefulness of the suggested framework in practice and a survey to gather industry opinions, which will be analyzed in this chapter.

In order to collect both quantitative and qualitative information from industry professionals regarding the advantages, difficulties, and real-world applications of automating the financial dunning process through the integration of machine learning, the survey was created using a systematic methodology. A Proof of Concept (PoC) was suggested as a technical research instrument to demonstrate the viability and functionality of the suggested framework in light of the findings. With a combination of theoretical alignment with the research aims and empirical validation, this dual-tool approach guarantees that the study offers a thorough grasp of the issue.

To approach the topic methodically, the authors adhered to a set of exacting protocols that comprised both research and practical application. The adopted methodology is presented in the following steps: (Oana-Alexandra Dragomirescu, 2025)

I. Review of Current Research and Literature

The first step was to perform a thorough examination of the body of existing literature in order to comprehend the present status of dunning automation research and implementations. The authors looked at various strategies, tools, and designs employed in related projects, as well as the challenges faced by other practitioners and researchers.

II. Performing a Survey to Gather Empirical Data

To learn more about the existing management of the dunning process, a survey was created and sent to financial and IT personnel. The survey sought to ascertain the extent of machine learning technology deployment in this context as well as the primary automation-related requirements, expectations, and problems.

III. Examining Current Solutions and Finding Development Possibilities

Existing technical solutions and their feasibility for incorporation into an automated dunning workflow were assessed using the data gathered from the survey and literature review. Through this study, we were able to pinpoint the shortcomings of the existing solutions and provide a fresh approach that would satisfy present demands while enhancing process effectiveness.

IV. Designing and Developing a Proposed Architecture

An architecture that blends machine learning techniques with the conventional dunning process was suggested using the data acquired. By offering a framework that tackles existing inefficiencies and connects theoretical ideas and real-world financial automation applications, the suggested architecture seeks to streamline the dunning process while ensuring scalability, compliance, and continuous improvement.

V. Testing and Validating the Solution

Several dunning scenarios were assessed to guarantee the solution's accuracy. This step laid the foundation for future enhancements by observing the architecture's benefits and drawbacks.

VI. Reflection and Conclusions

The key findings were outlined in the final report, along with the benefits of automating the financial dunning process with the suggested methodology. Additionally, recommendations for potential future uses and lines of inquiry were made to advance this discipline.

Survey

To collect qualitative data, the survey—one of the technique techniques utilized for this paper—was selected as the main starting point. We were able to compile participant perspectives, in-depth data, and insights by conducting this survey, which enabled us to gain a thorough grasp of the subject. The aim of this survey is to gather insights from 77 professionals across various industries regarding the current state of the dunning process, its challenges, and potential improvements through automation and Machine Learning (ML). By analyzing the responses, the study aims to identify pain points in existing dunning practices and explore how ML-driven automation can enhance efficiency, customer experience, and financial outcomes.

Both structured and open-ended survey questions were used, allowing participants to freely express their thoughts while adhering to predefined themes and sequence. According to the study's objectives, open-ended questions enable participants to offer more thorough and customized feedback.

With an emphasis on respondents' backgrounds, knowledge with dunning, present difficulties, possible solutions, and future trends, the survey aims to gather information about the dunning process. First, demographic and professional information is gathered, such as industry, role, years of experience, and the financial or ERP systems utilized. This aids in placing answers in context according to the participants' knowledge and experience with accounts receivable procedures.

It then evaluates respondents' dunning knowledge and experience by looking at how they have interacted with dunning notices, what tools they have utilized, and how effective they believe dunning tactics to be. To create a baseline understanding of the procedure and its effect on collections, it also looks at typical causes of late payments.

The study then looks into the main issues with the current dunning procedure, including operational bottlenecks, time-consuming procedures, and communication problems. The study is to identify areas that need improvement and evaluate how automation could increase efficiency by identifying these pain points.

Additionally, respondents are questioned about possible improvements, especially in automation area. This includes determining which dunning tasks would be most suited for automation, what features would enhance the efficacy of a dunning tool, and their opinions regarding the application of machine learning to collection optimization. The influence of current automation technology installations is also examined in the survey.

The study concludes by examining the dunning process's future and compiling opinions on potential developments over the ensuing ten years. It looks at the significance of customer experience in collections, the use of data analytics, and potential innovations that could change the industry.

Proposed solution

The second technique used in this research is the development of a software solution that incorporates the theoretical insights from the entire analysis and the results of the survey. The main purpose of this prototype is to demonstrate and validate the practical applicability of the proposed framework.

The first concept we are discussing in this section is the Proof of Concept (PoC) designed as a scalable, and adaptable infrastructure that enhances existing invoice processing applications using a dunning approach without replacing them. (Oana-Alexandra Dragomirescu, 2025) This software tool incorporates key elements for automating the invoicing process, minimizing human errors and resource loss, such as time, while also featuring functionalities like data analysis using Machine Learning to classify clients based on their risk levels.

As a result, the dunning process is tailored for each client according to their payment history and delays. Depending on the identified risk level, a customized approach is applied for each client: more serious clients will receive friendlier, less frequent reminders, whereas clients with higher risk will get more frequent, urgent reminders across multiple platforms like SMS or email.

The system is built based on several modules, as follows:

- Initial Research and Market Analysis is the module where market research is conducted, user requirements are identified, and existing dunning strategies are analyzed to determine the most effective approaches.
- ML Algorithm Research and Model Definition involves researching and selecting suitable Machine Learning algorithms for customer segmentation and personalized notifications, as well as defining the model architecture.
- Data Collection and Preprocessing focuses on gathering historical data on payments and user behavior, followed by cleaning and preparing the data for training the ML model.
- Model Training, Testing, and Optimization is dedicated to training and validating the Machine Learning model, optimizing its performance to ensure accurate customer segmentation.
- Automated Risk-Based Customer Segmentation is the module where users are classified based on their likelihood of payment, creating risk-based segments that allow for differentiated strategies.
- Personalized Notification Strategies and Automation manages the generation of tailored messages for each customer segment, using different tones (friendly, neutral, firm) and automating notification delivery across multiple channels.
- Application Development and ML Integration focuses on developing the application itself, implementing the interface for administrators and operators, and integrating the ML model with the notification system.
- Real-Time Notification Tracking and Analytics ensures real-time monitoring of notification delivery, opening rates, and overall effectiveness, providing detailed insights into the success rate of each strategy.
- End-to-End Testing and Optimization verifies the full functionality of the system, testing the entire dunning process and refining strategies to improve payment recovery rates.
- Evaluate the Results and System Evolution is the module dedicated to analyzing system performance and continuously adapting the ML model, refining notification strategies, and implementing improvements based on updated data.

An important aspect to mention is that the demonstrative model described so far is still under development and is not in its final form. Its purpose is to highlight and address the theoretical aspects analyzed in the initial chapters of the research, serving as a viable starting point for developing a much more complex solution.

The proposed framework illustrates how companies can leverage cutting-edge technologies to improve operational efficiency while meeting the demands of a globally connected and resource-conscious economy.

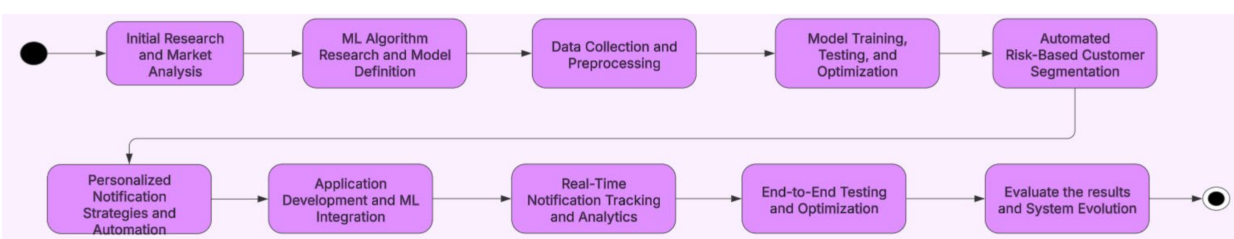

Figure 2. The workflow of the proposed solution

Reference: Authors' own research.

Results

The results presentation is grouped in two subsections. The first one examines the survey data and offers insights into the potential and problems associated with the implementation of ML and dunning automation. To solve the highlighted inefficiencies, the second section presents a Proof of Concept (PoC) system that combines machine learning with dunning process automation.

Results of survey

The survey was divided into five major areas, as mentioned in the preceding chapter, and the responses will be further examined using this structure.

A stratified sampling technique was used to choose survey respondents to guarantee a representative sample of people with different degrees of experience with machine learning and automated invoice processing.

The first section's focus was on the respondent's background and experience in the field. Most responders are employed in IT-related domains, such as cybersecurity, data analytics, artificial intelligence, and software development. Accounting and finance also contribute significantly. Many of the respondents work as analysts, consultants, and developers, although their duties vary greatly. Although a wide number of businesses are included by the poll, the most represented industries are IT and finance, followed by retail, SaaS, financial services, and fintech. 23 of responders had four to six years of experience, 16 have zero to two and 12 two to four years. Fewer individuals have more than eight years of expertise.

While 14 respondents have not been directly or indirectly involved with accounts receivable procedures, the majority (57 respondents) have. The most used systems in respondent's organizations are the ones from SAP (36 respondents), followed by the tools created by Oracle (13), Microsoft-based systems (9), and few mentions of QuickBooks, Workday and custom software solutions. Figure 4 was created to illustrate that the primary used ERP or financial system in organization are the ones created by SAP.

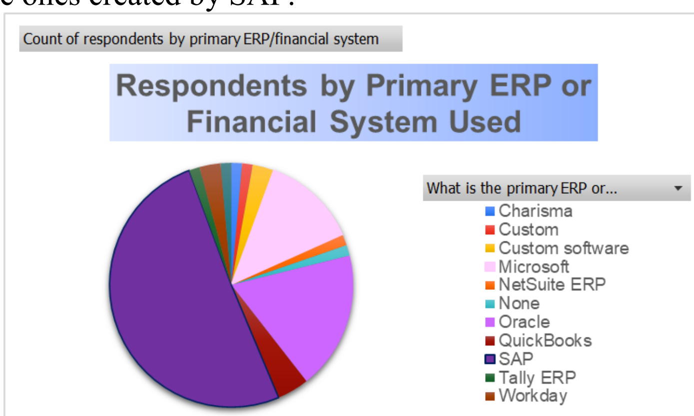

Figure 3. Most used ERP software

Reference: Authors' own research.

Most respondents have little firsthand exposure to the dunning procedure from the payer's point of view because they have never received a dunning notification as consumers. Nonetheless, dunning has been used professionally by many. The most popular tool for managing dunning is SAP, while some people suggested utilizing specially designed software. In the process, they are responsible for addressing consumer communications, assessing past-due bills, and creating notices. Most respondents gave dunning a rating of three to four on a five-point scale, which indicates modest performance but room for improvement, when asked how effective it is at recovering past-due payments.

The typical responses of customers to dunning notices were also investigated in the survey and illustrated in Figure 5. Payment delays or no answer at all are the most frequent responses (33 people responded with "delayed" and 18 are getting "no response" from the customer). When consumers do reply, they frequently state that the main causes of late payments are simple error, disagreements over invoicing, or financial concerns. Many clients choose to escalate disputes or postpone responding to notices instead of paying right away.

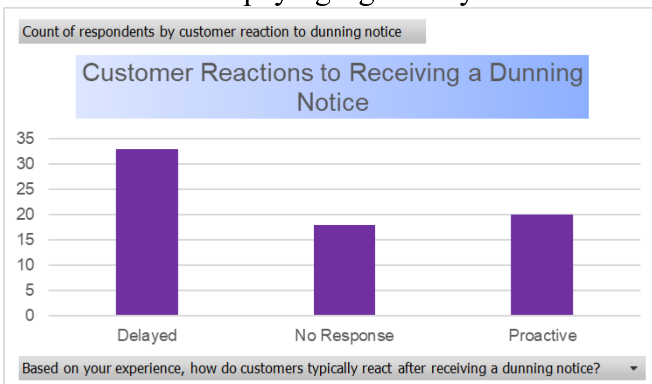

Figure 4. Customer reactions on dunning notices

Reference: Authors' own research.

Respondents cited the considerable human labor required, ineffective customer communication, and inconsistent follow-ups as the main issues with the existing dunning procedure. The improper segmentation of clients according to risk levels is also a major problem. Creating notices, monitoring payments, and resolving customer disputes are the dunning process's most time-consuming activities. Since clients frequently disregard or postpone responses, communication is still one of the key problems. Furthermore, disagreements over invoices usually necessitate lengthy conversations, and the process feels impersonal and inefficient when there is a lack of individualized communication.

Respondents recommended boosting automation in crucial areas including notice sending, response tracking, and customer behavior analysis to enhance the dunning process. Additionally, they suggested using sophisticated analytics to enhance collection operations and improving customer segmentation to target high-risk customers. They ranked notice creation, customer segmentation, and payment tracking as the three areas of the dunning process that would most benefit from automation.

The characteristics that respondents believed would increase the effectiveness of a dunning tool were also discussed. Real-time tracking, customized communication formats, and language assistance are the most often cited features. By anticipating consumer behavior, identifying high-risk accounts, and maximizing the timing of dunning communications, machine learning, according to most respondents, may greatly improve the dunning process. Some businesses have previously thought about or used robotic process automation (RPA), artificial intelligence (AI), or machine learning in their dunning procedures, with good results like increased customer satisfaction, decreased manual labor, and higher recovery rates. 66 of the people answered affirmative when asked if Machine Learning could enhance the dunning process (Figure 6).

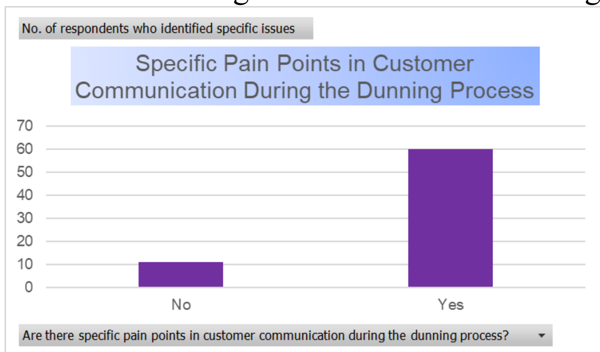

Figure 5. Pain points in customer communication

Reference: Authors' own research.

Respondents anticipate that the dunning procedure will undergo a substantial change in the upcoming five to 10 years. They anticipate that everyday jobs will require less human participation because of growing automation and AI integration. Many people think that data-driven, targeted dunning tactics will increase productivity and client interaction. Respondents underlined the value of data analytics in predicting payment delays, enhancing client segmentation, and streamlining collection tactics.

Finally, when asked about the importance of customer experience in the dunning process, most respondents (38 rated with 5 and 31 with 4) rated it between four and five on a five-point scale (Figure 7), indicating that ensuring a smooth and customer-friendly process is a key priority. Overall, the findings suggest that the dunning process remains largely manual and inefficient, leading to delays and ineffective collections. Machine learning and automation have the potential to revolutionize the process by predicting payment behavior, optimizing communication timing, and improving segmentation. As businesses move toward AI-driven dunning strategies, the future of collections will likely see greater efficiency, improved recovery rates, and enhanced customer satisfaction.

Figure 6. Importance of customer experience in dunning

Reference: Authors' own research.

According to the survey's findings, the dunning procedure is still mostly done by hand and is inefficient, which causes responses to be delayed and collections to be ineffective. Through better segmentation, communication timing optimization, and payment habit prediction, machine learning and automation could greatly improve the process. Future collections will probably be more efficient, have higher recovery rates, and provide a better customer experience as companies shift to more automated, AI-driven dunning tactics.

Considering this, the following proposed IT solution bridges the identified shortcomings, transforming key concepts into an intelligent and robust framework.

A Proposed Framework for Dunning Automation

The well-designed application successfully fills in the gaps noted by auditors through surveys by converting the studied concepts into a dynamic, realistic solution. It displays a smart fusion of technological precision and creative design, intelligently addressing concerns including lack details, risk assessment, prediction, and customization.

In this context, the software solution is designed to automatically generate detailed invoices, which are then sent to clients through various communication channels, accompanied by representative messages at well-defined intervals, depending on the risk level associated with each client. This implementation is based on Machine Learning (ML), which is fundamental to conducting risk analysis and making predictions. Message personalization is achieved by classifying clients according to their risk profile, with high-risk clients receiving more frequent notifications across multiple channels with more urgent messages, while standard clients who pay on time receive fewer, more generic reminders.

This ML-driven analysis is carried out using specific algorithms tailored to data processing. Initially, a base model was created and tested with relevant data, undergoing training to reach a more complex and well-defined version. Relevant data is processed and trained to achieve a more refined and advanced version. During the training phase, cutting-edge ML frameworks like TensorFlow are used to build predictive models for invoice-related tasks, including classification, anomaly detection, and data extraction.

The notification system itself represents the dunning process, which includes both the underlying risk analysis, and the automatic generation of invoices and email details based on the user profile.

From the perspective of software architecture, the field has been explored in terms of existing models and the benefits of each. In general, there are numerous types of architectures, including: monolithic architecture, microservices-based architecture, layered architecture, event-driven architecture, peer-to-peer (P2P) architecture, service-oriented architecture (SOA), and MVC. Each of these addresses different needs and comes with specific advantages and challenges.

The first of these, monolithic architecture, is simple and efficient for small applications but becomes difficult to maintain as the application grows. In contrast, microservices offer modularity and scalability but require careful management of communication between services. Another important type is MVC, which clearly separates the application's logic from the user interface, facilitating maintenance and testing, but can become complex for smaller projects.

Regarding layered architecture, this is a classic choice for organizing functionalities within an application, offering a clear structure but may encounter performance issues due to communication between layers. For applications that require quick reactions to events, event-driven architecture allows decoupled communication between components but can become complex as the number of events increases.

Additionally, SOA is suitable for applications that require integration between various services, being easier to reuse, but can present challenges in integration and management. Finally,

peer-to-peer (P2P) architecture, used in decentralized applications, offers fault tolerance and scalability but can face difficulties in terms of security and node management. (Richards, 2015)
Based on the facts mentioned above, this software solution is built using the MVC (Model-View-Controller) model for several reasons, each of which highlights its advantages over other architectural choices.

First, MVC architecture offers a clear separation of concerns, dividing the application into three components: the model, the view, and the controller. This structure makes it easier to manage and scale the application as it grows. In contrast, other architectures like monolithic architecture do not provide such a distinct separation. This can lead to a tightly coupled system that becomes increasingly difficult to maintain and scale over time, especially as the application complexity increases. (Hasselbring, 2018)

Another key benefit of MVC is its maintainability. Changes to one component, such as the user interface (view), do not affect the other parts of the system (model and controller). This contrasts with microservices or monolithic architecture, where making a change in one part of the system often requires updates across the entire application or communication handling between services, which can complicate the process. (Lech Madeyski, 2005)
In terms of testability, MVC excels because the separation of its components allows for independent unit testing. For instance, the model can be tested without worrying about the view, and vice versa. While layered architectures also provide some level of separation, they can become cumbersome and less modular, making testing more complex as the layers interact.

Lastly, MVC enhances reusability. Its structure allows for components to be reused across different parts of the application, speeding up development and improving consistency. While architectures like event-driven or peer-to-peer (P2P) may excel in specific use cases such as real-time applications or decentralized systems, they introduce added complexity and are less suited for typical web applications that require clear user interface management and business logic separation. (Anubha Sharma, 2015)

The model is represented as an efficient framework that logically separates the application into three main components as already explained and below mentioned:

I. Model – Manages data structures and the database, storing essential information about clients, their payments, and other relevant data.

II. View – Consists of the pages and visual components that users interact with through a browser, displaying data received from the model in an intuitive format. User interactions can trigger actions that are then managed by the controller.

III. Controller – Acts as an intermediary between the Model and View, handling HTTP requests and routing. It retrieves data from the model and provides it to the View for display, either when loading components in the user interface or in response to user actions.

This structure enables efficient management of the dunning process, integrating risk analysis, automatic invoice generation, and personalized messaging into a cohesive and scalable solution.

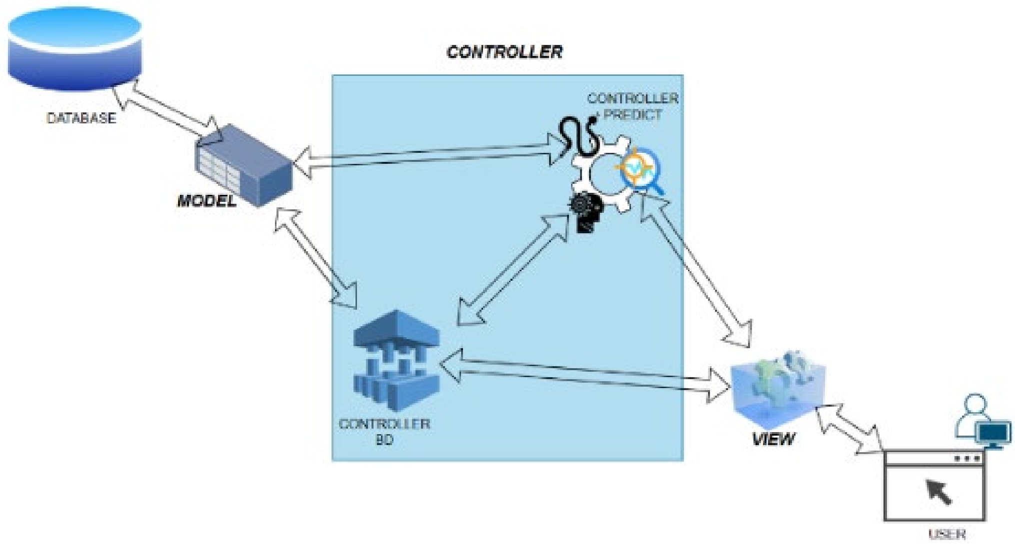

Figure 7. MVC architecture in the presented solution

Reference: Authors' own research.

As described in Figure 8, the process begins with billing data ingestion, which involves extracting and loading data from a non-relational database. First, the database is connected to the Model component, from which the data is transferred to the other components via a RESTful service. These data are managed by two separate controllers, each with a distinct role: the Data Processing Controller, responsible for CRUD (Create, Read, Update, Delete) operations and the initial analysis of stored database records; and the Risk Analysis Controller, implemented in Python with TensorFlow, dedicated to running machine learning models for risk scoring and optimizing the notification strategy. For better scalability and processing efficiency, these controllers were deployed on separate servers. This decision was made to isolate the intensive ML processing from transactional database operations, thus reducing API response times and preventing bottlenecks caused by complex queries.

The View component handles the presentation of information to the user, providing a clear and user-friendly interface for visualizing the results of data processing and risk analysis. It interacts with the controller to display the relevant data, enabling users to make informed decisions based on the results.

After data ingestion, it undergoes a rigorous cleaning and preprocessing stage to ensure completeness, consistency, and the absence of anomalies. Any detected inconsistencies are corrected through standardization, preparing the dataset for further analysis.

A crucial component of this process is automated invoice generation, which includes payment details and associated delays. If errors occur during data retrieval, an automatic reprocessing mechanism is triggered to maintain data accuracy and integrity.

To ensure feature uniformity, StandardScaler is applied to normalize variables, improving model stability and performance. Additionally, to address class imbalance, the SMOTE (Synthetic Minority Over-sampling Technique) is used, generating synthetic samples for the minority class. This prevents model bias and ensures a balanced data distribution. (Md Manjurul Ahsan, 2021)

Once the dataset is prepared, the model training phase begins, employing various classification techniques to ensure precise and generalizable predictions. Algorithm selection was based on their performance in similar contexts and their ability to handle imbalanced data effectively.

The model training phase employs multiple classification techniques to ensure precise and generalizable predictions. Random Forest is used to handle class imbalances and capture complex relationships between features by leveraging multiple decision trees, thereby improving accuracy. Logistic Regression, a widely recognized technique for its interpretability, is applied to construct a simple yet effective model with balanced weights. Support Vector Machine (SVM) with a linear kernel is implemented to maximize the separation margins between classes and adjust their significance, making it particularly effective in distinguishing data points. Additionally, K-Nearest Neighbors (KNN) classifies observations based on their proximity to neighboring points, where an optimal selection of the hyperparameter k helps reduce errors in imbalanced datasets. (Manish Suyal, 2022)

To further enhance model accuracy, Ensemble Learning is integrated by combining two powerful techniques. Bagging, implemented through Random Forest, mitigates overfitting by aggregating multiple decision trees and utilizing balanced weights for classification, leading to more stable predictions. Meanwhile, Boosting, specifically using XGBoost, iteratively corrects errors in previous models and improves overall model performance. Through this combination of methods, the final model achieves superior accuracy, stability, and the ability to generalize effectively on imbalanced datasets.

By combining these methods, the final model becomes more accurate, stable, and capable of handling imbalanced datasets efficiently, ensuring reliable predictions.

After model validation and achieving a high level of accuracy, it is used for risk scoring of each customer, identifying the likelihood of payment delays. Based on these predictions, a personalized notification strategy is applied and optimized as follows: high-risk customers receive more frequent messages across multiple communication channels to increase the chances of payment recovery, while low-risk customers receive fewer notifications, limited to simple reminders, encouraging timely payments.

Through this automated process, customized invoices and notifications are generated, optimizing both message content and frequency for better customer relationship management.

To maintain model performance over time, it is continuously monitored, considering that financial data is dynamic and constantly changing. New payment records, delays, or even early payments can affect model behavior, requiring periodic retraining.

Additionally, the separate server architecture allows for better resource management, preventing bottlenecks and optimizing system scalability. The dedicated data processing server ensures constant integrity and database updates, while the risk analysis server allows for intensive ML algorithm execution without affecting the primary system's performance.

By integrating advanced Machine Learning technologies, utilizing a scalable system, and applying an efficient notification strategy, the dunning process has been significantly optimized. This approach enables more effective debt collection, reduces delays, and personalized customer communication, ultimately improving cash flow management and enhancing the company's financial stability.

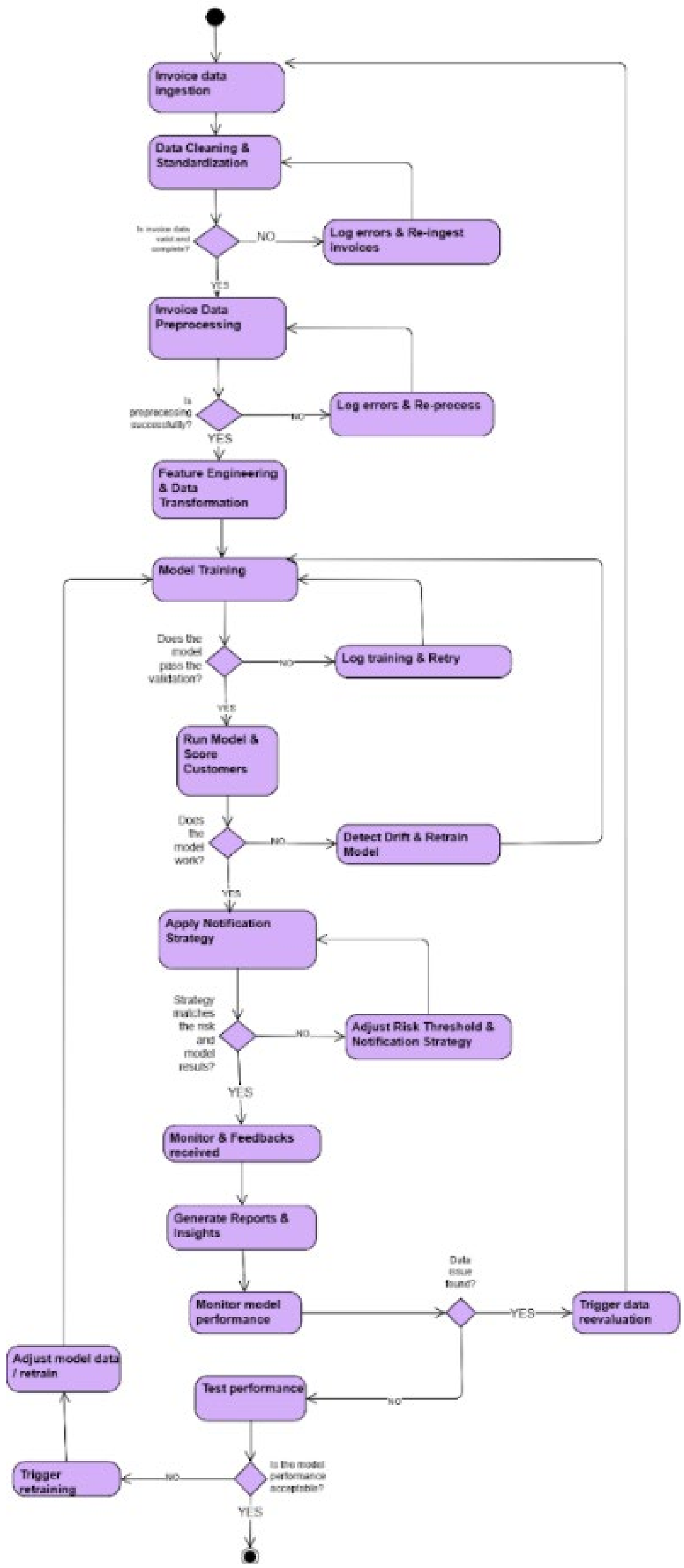

Figure 8. Framework for ML-based PoC

Reference: Authors' own research.

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Conclusion

In a dynamic financial environment, managing payment delays and optimizing the debt collection process are essential for a company's economic stability. Implementing an automated notification system based on Machine Learning (ML) enables a more precise and efficient approach, reducing delays and personalizing communication with customers.

The study's conclusions emphasize how crucial is the automation of the financial dunning procedure. According to the survey's findings, most businesses continue to use manual or partially automated dunning procedures, which leads to inefficiencies, late payments, and erratic customer service. Customers frequently ignore or put off responding to dunning notices that lack appropriate segmentation and tailoring, which further lengthens the debt collection cycle. Additionally, automation can greatly streamline the most time-consuming dunning processes, including notice creation, payment tracking, and dispute resolution.

This article aims to highlight the existing gaps in the financial sector regarding the dunning process and propose solutions such as increasing recovery rates, reducing manual work, and improving customer satisfaction through ML integration in dunning.

As a complex process, dunning presents certain challenges that ML could help overcome. Therefore, this study focuses on the advantages that ML brings in this context. Among the main issues identified in dunning are high costs, inefficient customer segmentation, unoptimized communication strategies, and poorly timed notifications. From this perspective, the analysis was conducted considering ML integration, which is seen as a viable solution for process improvement.

To achieve this goal, a detailed theoretical analysis of the dunning process was conducted, identifying key deficiencies, relevant ML algorithms, and their benefits, especially how ML integration enhances dunning. According to the research findings, this leads to better data analysis and the ability to make predictions that optimize the financial dunning process.

Following this theoretical analysis, two practical techniques were applied to support the benefits of using ML in the dunning process.

The first technique involved a survey. The results confirmed that the process is largely manual and inefficient, leading to delayed responses and insufficient debt collection. ML integration, through more precise segmentation, optimized communication scheduling, and payment behavior prediction, can significantly improve efficiency. As companies adopt AI-driven automated strategies, collection methods are expected to become more effective, achieve higher recovery rates, and enhance the customer experience.

The second technique involved conducting a practical demonstration based on the conclusions of previous analyses. A software solution was developed that utilizes ML algorithms to segment customers and predict risk levels. Based on these predictions, each customer is assigned a personalized strategy tailored to their risk profile. To ensure maximum efficiency, the most advanced ML algorithms were used, according to research findings.

As a result of the entire research process, integrating Machine Learning into the dunning process not only optimizes debt recovery but also redefines companies' financial strategies. Through advanced data analysis and decision automation, ML enables prompt and efficient interventions, reducing both financial losses and operational costs. One important step in modernizing accounts receivable management is the incorporation of machine learning into dunning automation.

In the future, it is anticipated that the dunning process would become more autonomous, and data driven. Organizations can use AI and ML developments to go beyond reactive collections and adopt proactive tactics that anticipate and stop late payments before they happen. In addition to lessening the operational load, automation will increase financial stability and recovery rates.

The limitations of this research will be addressed in future studies, aiming for a more detailed analysis of the model's performance. It is essential that the model remains feasible and valid, considering not only customers' payment behavior but also other relevant characteristics. Additionally, as the solution is used over time, its reliability will become clearer, and continuous training will generate increasingly accurate results. As future directions, the next main objective represents integrating this solution into a real economic framework with a larger volume of data.

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Appendix

Survey questions:

1. What is your current field of work?
2. What is your current role in the organization?
3. What industry does your organization belong to?
4. How many years of experience do you have in your field?
5. Have you had any direct or indirect involvement with accounts receivable processes?
6. What is the primary ERP or financial system used in your organization?
7. Have you ever received a dunning notice or email as a customer?
8. Have you worked with the dunning process in a professional capacity?
9. If yes, which tools or systems have you used for managing dunning?
10. If yes, what were your main responsibilities in the dunning process? (e.g., Drafting notices, analyzing overdue accounts, customer communication, etc.)
11. How would you rate the overall effectiveness of the dunning process in recovering overdue payments?
12. Based on your experience, how do customers typically react after receiving a dunning notice?
13. What are the most common reasons customers provide for late payments? (e.g., Financial difficulties, disputes over invoices, oversight, etc.)
14. In your opinion, what are the main challenges with the current dunning process?
15. What are the most time-consuming tasks in the dunning process? (e.g., Preparing notices, tracking payments, resolving disputes, etc.)
16. Are there specific pain points in customer communication during the dunning process?
17. If yes, please describe which pain points.
18. What improvements would you suggest for the dunning process?
19. Which aspects of the dunning process do you believe would benefit most from automation? (e.g., Notice generation, customer segmentation, payment tracking, etc.)
20. What factors or features would make a dunning tool more effective? (e.g., Multilingual support, customizable templates, real-time tracking, etc.)
21. Have you considered or implemented any new technologies (e.g., ML, AI, RPA) to improve the dunning process?
22. Do you think Machine Learning (ML) could enhance the dunning process?
23. If yes, in what ways could ML be applied to the dunning process? (e.g., Predicting customer behavior, identifying high-risk accounts, optimizing communication timing, etc.)
24. Are there specific features or tools you think should be added to existing dunning systems? Please describe them here.
25. If yes, what were the outcomes? (e.g., Improved recovery rate, reduced manual work, enhanced customer satisfaction, etc.)
26. How do you see the dunning process evolving in the next 5–10 years?
27. What role do you think data analytics will play in shaping the future of dunning?
28. How important is customer experience in the dunning process?
29. Do you have any other thoughts or feedback regarding dunning process automation?