FinTech

Article

Examining the Plausible Applications of Artificial Intelligence & Machine Learning in Accounts Payable Improvement

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Abstract: Accounts Payable (AP) is a time-consuming and labor-intensive process used by large corporations to compensate vendors on time for goods and services received. A comprehensive verification procedure is executed before disbursing funds to a supplier or vendor. After the successful conclusion of these validations, the invoice undergoes further processing by traversing multiple stages, including vendor identification; line-item matching; accounting code identification; tax code identification, ensuring proper calculation and remittance of taxes, verifying payment terms, approval routing, and compliance with internal control policies and procedures, for a comprehensive approach to invoice processing. At the moment, each of these processes is almost entirely manual and laborious, which makes the process time-consuming and prone to mistakes in the ongoing education of agents. It is difficult to accomplish the task of automatically processing these invoices for payment without any human involvement. To provide a solution, we implemented an automated invoicing system with modules based on artificial intelligence. This system processes invoices from beginning to finish. It takes very little work to configure it to meet the specific needs of each unique customer. Currently, the system has been put into production use for two customers. It has handled roughly 80 thousand invoices, of which 76 percent were automatically processed with little or no human interaction.

Keywords: accounts payable; purchase order; invoice; artificial intelligence; machine learning; automation

Citation: Kanaparthi, V.K. Examining the Plausible Applications of Artificial Intelligence & Machine Learning in Accounts Payable Improvement. *FinTech* **2023**, *2*, 461–474. https://doi.org/10.3390/fintech2030026

Academic Editor: Yokyen Nguwi

Received: 8 March 2023
Revised: 24 June 2023
Accepted: 3 July 2023
Published: 13 July 2023

1. Introduction

A client's cost arbitrage with the finance department is no longer possible [1–3]. They are now seeking novel solutions that provide cost benefits and add value [1–3]. Automating processes is critical for businesses trying to save expenses [4,5]. What and how should be automated is the question. Finding repetitious jobs that can be automated using robots and automation scripts has traditionally been the norm [6,7]. Businesses are gradually looking at automation prospects that involve significant cognitive burdens [8]. Machine learning (ML) algorithms are one of the leading technologies used to automate scripts to make them work as well as or better than people while being more efficient [9]. The transformation of accounts payable from a cost center to a profit center is one area where ML is progressing. While Bohn (2010) correctly noted that technology holds the key, the problem faced by industry observers is that there is not a "one size fits all" answer, leaving different businesses and departments to put together their tools and solutions that could increase efficiency.

One financial operation that relies heavily on human labor is accounts payable [10]. The procedure includes obtaining raw materials, services, and products from the listed vendors and paying their bills by the due dates specified in the contracts. Accounts payable involves receiving invoices from suppliers, using dynamic business rules to match vendor information on the invoice to corporate data, and finally putting the invoices in the enterprise resource planning (ERP) system so they can be paid [10]. This procedure could include certain conditional phases depending on the customer and the kind of bills. Checking business rules for compliance with invoices, matching invoice line items (i.e., performing a three-way match between the line item descriptions, Purchase Order (PO), and Products Receipt), and giving the process a tax code for each item are among these tasks [11]. To preserve a long-term connection with the suppliers and prevent fines, managing accounts payable is also a crucial but difficult responsibility [12]. Invoices must be paid correctly and on time. The difficulties are made more complicated since it must be made sure that duplicate, inaccurate, and fraudulent invoices are not paid [13,14]. Doing so would cause losses and increase the expense of recovering such payments.

The industry is heading toward incorporating artificial intelligence (AI) and ML models into various business processes [15]. The ML models do, however, have a warning. Despite having a very high level of accuracy, a model's predictions are not always accurate [16]. Therefore, explanations that fit the estimates are crucial. In addition, a system that automates may look at specific thresholds that, if met, will automate a particular process step [17].

Additionally, the ML models must adapt to processes with dynamic rules. For example, tax legislation may change depending on the policies [18]. Due to this, there is an increasing need for models that can automate a process and learn and assess the factors and thresholds they consider for a particular projection [10]. For quite some time, experts in the field of labor economics have been engaged in discussions about the vulnerability of occupations focused on routine-driven tasks to be replaced or significantly impacted by technological advancements and automation [19–24]. It is hardly surprising that professions like bookkeeping, particularly those involved in handling and overseeing accounts payable, are more prone to such changes driven by technology. However, recent studies have indicated that introducing new accounting regulations increases the demand for skilled accounting personnel [25]. Given the critical nature of ongoing discussions surrounding automation and its potential consequences for employment markets, the authors must explore how integrating artificial intelligence within accounts payable management can impact job prospects for accounting professionals and bookkeepers. In the end, the application of AI within the realm of accounts payable administration pertains to the influence of accounting and financial reporting on the production input market, which includes labor and capital [26,27].

AI and ML are the most emerging fields that focus on automating the process by learning from previous data and predicting future outcomes. ML algorithms take the earlier data as input and provide the predictions as the output by discovering the hidden insights from the data. AI and ML are used in various fields like education [28], image processing [29], risk prediction [30], indexing [31], and many more.

This research employs AI-powered micro-services to streamline the time-consuming task of processing the bills and automatically sending invoices with minimal human intervention. The use of AI helps to boost efficiency and cuts costs, making customers and suppliers happier. Thus, the significant contribution of the research is given below.

- The research proposes an automated invoice processing system that utilizes AI-based modules for various stages of the invoice processing pipeline. This system aims to reduce manual labor and improve efficiency in the accounts payable process.
- The proposed system has been put into production use for two customers and has processed approximately 80 thousand invoices, with 76 percent being automatically processed with little or no human interaction.
- The research addresses the challenges in accounts payable, such as manual validation checks, mismatches in catalogs, duplicate invoices, changing tax codes, and the need for a client-wide generalizable solution. The proposed system overcomes all these.
- The study highlights the importance of AI and machine learning models in automating business processes and emphasizes the need for explainable AI and the ability to adjust to changing rules.
- The research discusses the risk management aspect of accounts payable and proposes an automated risk detection system to identify duplicate and fraudulent invoices, which can help prevent the same payments and reduce financial losses.

2. Materials and Methods

2.1. Study Background

Accounts payable constitutes a key facet of an organization's financial management infrastructure, encompassing the systematic processing, monitoring, and remittance of outstanding liabilities to suppliers and vendors [32–34]. The contemporary business ecosystem's increasing interconnectedness necessitates the development of sophisticated and precise approaches to managing payables, prompting the emergence of innovative practices and technological breakthroughs aimed at refining the AP process [35]. A prominent paradigm shift in accounts payable is the advent of digital solutions and automation, which have engendered a transformative impact on organizational AP management. The incorporation of cutting-edge technologies, such as artificial intelligence (AI), machine learning, and robotic process automation (RPA), has heralded a new era in which enterprises can diminish manual procedures, curtail inaccuracies, and bolster overall efficacy [6,13,36]. Moreover, adopting cloud-based platforms and electronic invoicing (e-invoicing) has enabled seamless interfacing between distinct departments and stakeholders, augmenting visibility and command over the AP lifecycle [17,37]. Contemporary accounts payable management practices extend beyond technological advancements to optimize working capital and cultivate robust supplier relationships. Organizations can streamline cash flow and forge mutually advantageous partnerships with their suppliers [34,35] by harnessing dynamic discounting and supply chain financing techniques. As the accounts payable landscape undergoes continuous metamorphosis, keeping abreast of emergent trends and best practices will prove indispensable for organizations aspiring to maintain a competitive edge in the rapidly shifting business milieu.

2.2. Process for Accounts Payable

The accounts payable procedure is manual, mainly in current affairs. Since no unified platform facilitates hands-free invoice processing from receipt through payment, agents carry out most of the work in the invoicing process [17]. The accounts payable agent or accountant manually examines and verifies each new invoice to ensure it has all the necessary information and fields [38]. When an invoice comes in, the agent has to figure out whether it was based on a purchase order (PO) or not [17]. An invoice for goods based on a PO was issued before the actual transaction instead of a Non-PO-based invoice, created after the business had utilized the services [17]. If the invoice is based on a purchase order, the agent checks to see if the corresponding PO number exists in the PO database [1]. The billing address and if the invoice is invoiced to the receiving firm are two other examples of these validations.

Depending on the circumstances, further approvals for the cost and date of the invoice and many more may be required. Following these preliminary verifications, the agent identifies the vendor by cross-referencing the invoice's details against vendor records, such as the vendor's identity, location, and financial data [1]. Henceforth, each piece of information in the system is entered manually. The line items that make up a PO invoice are compared to the receipt of the goods, taking into account the line items' descriptions, quantities, prices, etc. The next step is for them to determine the appropriate tax code and account coding for processing a Non-PO invoice. After that, the invoice is submitted to ERP to be paid. It's also possible that many files and data will need to be retrieved from external sources, such as other applications and data repositories. Robotic process automation (RPA) has been used to streamline certain payments, depending on the nature of the customer and the invoices themselves.

Having a system that can be utilized simply by many customers with various settings for invoice processing is difficult at the moment. In addition, due to the following problems, the processes involved in processing invoices are laborious, time-consuming, and complex. The problems include:

- *Mismatch in catalogs*: Since purchasers and sellers maintain catalogs, the same item is described using several terms. As a result, there may be a discrepancy between the line item descriptions in the invoice and the PO for the same item while generating bills. On the other side, different things could be mistakenly classified as the same, and payments might be issued in error.

- *Shortened names*, such as *Butter* vs. *Bttr*, etc., introduced by either the customer or the vendor makes it impossible for RPA or other classic automating approaches to do the line-item matching.
- *Duplicate invoices*: Merchants may resubmit specific invoices due to a delay in payment or other circumstances.
- *Double payments*: Due to the repeated entry of the same invoice into the system, the organization may pay the invoice more than once.
- *Tax code and rules*: As regulations change over time, the tax code for a particular item (or set of items) may also vary. This raises a problem since the earlier information would therefore be unnecessary.
- *Client-wide generalizable solution*: Different customers and sectors have various requirements for invoice compliance. Due to the nature of invoicing, certain businesses could also need simply a portion of the activities. For instance, item-based firms can only accept invoices based on purchase orders. Therefore, companies don't have to adhere to rules like using accounting codes for future projections. Therefore, finding a solution that can be used universally across several accounts is difficult.
- *Knowledge Retention*: Operators and partners typically consult Subject Matter Experts (SME) or paying consumers to answer complex questions. Attrition may cause knowledge loss if there is no system in place to record this user data and comments.

There is no affordable platform that allows for touch-free operation. To our knowledge, accounts payable is broadly applicable and readily configurable across various configurations for invoice processing.

2.3. Structure of the Accounts Payable System

The many components that are accessible and a potential workflow that might be organized in the system are shown in Figure 1. This part will discuss each element in depth. The system is designed with multiple phases. The processing system's modules (risk management, business rules check, etc.) can be run in whatever order that best suits the needs of the enterprise.

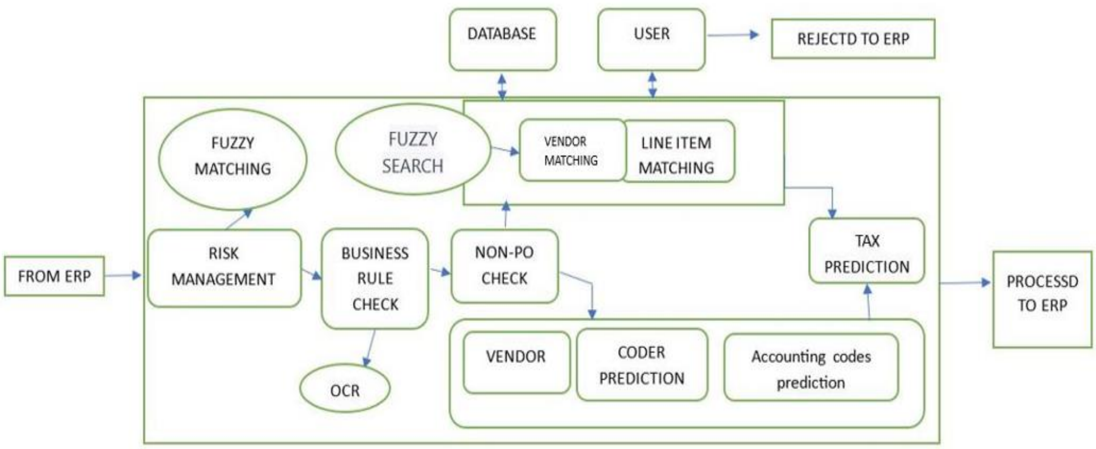

Figure 1. Schematic architecture of the proposed system.

2.4. Orchestrator

The system's orchestrator is primarily utilized for deploying and administering different services. It offers choices to define default settings for a particular service and a mechanism to select a specific service. Users may define business rules such as permitted price variation, other parameters, and the default thresholds for all AI components. As the system processes more and more invoices over time, customers may modify the thresholds at any moment by changing them. For this, it uses Node-red, an open-source browser-based flow editor. For each service, a unique node-red node is present in the implementation. The nodes have pre-configured default settings for the services that may be changed after deployment.

2.5. Risk Management

In accounts payable, duplicate invoice payments are a frequent occurrence. Companies often repeat payments by 0.1 to 0.5 percentage points. For a big business, this may amount to enormous sums. For a massive corporation with a $500 million yearly revenue, this percentage equates to a staggering $500,000 to $2.5 million. It is difficult to check and verify all the invoices with the available staff and resources. ERP systems can identify precise duplicates but not tampered copies.

Most businesses confirm invoices by invoice number, date, and amount. It is simple to avoid these built-in controls, whether on purpose or by mistake. Examples of situations where someone might wind up making a duplicate payment are as follows: misspellings on the invoice number; the vendor may issue a subsequent invoice with a different due date or an upset billing total, regardless of how tiny; multiple locations and channels may be used to submit duplicate invoices; utility bills (recurring payments) could not be sent as an invoice but as a statement, etc. The standard AP procedure is to input them as 76543Feb2023, account#+month+year. The risk of duplication increases if the AP auditor types 76543Feb2023 instead than 76543Februray2023 [39,40]. The manual search for possibly duplicate invoices consumes many resources. We suggest using an automated risk detection system to watch for duplicate and fraudulent invoices during transactions. Invoice number, name, amount, and date are the four criteria used to look for duplicate invoices in the system's historical invoice database [41]. The method for determining the individual parameter score is implemented as follows:

2.5.1. Invoice Number

Recognize invoices by their nearly matching invoice numbers. Invoice numbers are alphanumeric strings; therefore, fuzzy matching uses string sequences and the number field [41]. For example, the invoice numbers INVNO12345678 and INV12345678 are identical since INVNO and INV are possible acronyms for invoice number and invoice, respectively. Exact matching alone is less effective than fuzzy matching for finding duplicates. To find typos and transpositions, invoice numbers are subjected to similarity analysis. We implemented string similarity using Python and the Levenshtein distance measure [41].

2.5.2. Vendor Name

To continue validating, we'll need to index vendor names alongside their properties and employ a fuzzy search strategy to uncover duplicate suppliers sharing similar information like addresses, phone numbers, names, taxes cards, financial accounts, and more. For the fuzzy search, the FuzzyWuzzy, a Python-based tool, is used to look up specific words.

2.5.3. Invoice Amount

Preprocessing involves removing everything that isn't a letter or number [41]. If the quantity matches precisely or if the percentage of variance is below a specified level, the algorithm awards a high score. Additionally, it is indexed as a string so that near-edit distance fuzzy matches can be made when mistakes are likely to be made. E.g., 1908 vs. 1980.

2.5.4. Invoice Date

The invoice date should be indexed as a string and a date object once string regularization has been performed. The risk score considers a precise date match and a fuzzy string match. To assign weights to each criterion and then aggregate the results. Then, they marked all bills beyond a particular threshold as suspicious and forwarded them to a professional for further examination [42]. By gaining insight into duplicate bills and payments, businesses may detect financial leakage, a scam, and abuse and recover lost funds. Next, the invoices will undergo additional checks to ensure their authenticity.

2.5.5. Business Rule Check

Paper-based invoice processing is still a barrier for many AP processing organizations, even though some suppliers have converted to digital or electronic invoices. To accurately process an invoice, it is required to properly remove the information from it. Modern Optical Character Readers (OCR) are accurate when reading digital files but only fair when reading scanned or handwritten invoices due to scanning and document quality issues.

2.5.6. PO Number Validation

This is a necessary procedure for invoices based on POs, as the PO number must be verified to ensure payment. The purchase order number on the invoice or subheader is used for this purpose. Our setup verifies a purchase order's validity by double-checking the number against the ERP's PO database. If the invoice is compatible with the ERP system, processing will continue. When a mismatch emerges, the AP team works with Procurement to identify if the invoice is correct or just a copy of a different PO.

2.5.7. Tax, Freight, & Total Amount Validation

The system employs numerous validations to filter out phony invoices due to the high error rate in these areas. Important rules are as follows: (i) Discard invoices whose sum is zero; (ii) Evaluate the total cost of the invoice in comparison to the sum of its line item costs; and (iii) Consider the tax and shipping charges. All line items on the invoice, including tax, shipping, and total, must add up to the same figure. (iv) Additional audits at the customer's request are also part of the business laws.

2.5.8. PO Invoice versus Non-PO Invoice Classification

This process is necessary for all vendors, whether working with invoices based on a purchase order. The next step involves settling on an approach to the invoice. Whether based on a purchase order or not, invoices require multiple processes before they can be paid [4]. Invoices not responding to a purchase order (PO) are often identified by a PO number. This isn't always the case, however. Customers who strictly adhere to the No PO, No Pay policy only pay bills from approved vendors or those below a predetermined threshold. In some cases, It may be necessary to decide based on other parameters, such as vendor information, shipment information, etc., to allocate it to the right procedure appropriately.

2.6. Provider Matching

Most companies want an AP process that includes a vendor validation step to ensure the submitting vendor is on their list of Approved Vendors [43]. This practice is implemented to halt fraudulent or wasteful spending. The AP team manually searches the Vendor Master File to complete this stage. There are several methods to verify the vendor for invoices that are not based on a PO Vendor matching for invoicing based on POs is pretty straightforward under the proposed system. Since the vendor ID is in the PO database, searching from the primary vendor record and comparing attributes like the vendor's bank account number on the invoice to the original file may be used to extract vendor information. Invoices not generated from purchase orders make it harder to identify vendors since vendor data from the invoice may contain unusual wording. This makes searching the vendor master record using the vendor's name a cumbersome process [4]. Most currently available enterprise resource planning (ERP) platforms do not provide fuzzy matching based on text.

Consequently, a synthetic search by indexing vendor data is implemented. The proposed system considers three pieces of information: The VAT id, the vendor's bank details, and the vendor's bank account. The seller's name, address, and contact details are all stored in one convenient place: The "vendor information" field. Bank account numbers and VAT IDs are checked in the database exactly, whereas vendor information is compared using a fuzzy approach. A custom script called FuzzyWuzzy [39] is utilized to conduct fuzzy matching. This script compares two strings using the Levenshtein distance, the edit distance.

2.7. Aligning Line Items

Hosseini et al., (2020) [43] state that aligning line items is a major time sink when dealing with a PO invoice. During a line-item match, you'll double-check that the items on your bill match what you bought and maybe even see if they match what was delivered--all in the name of accuracy. Two-way matching involves checking the details of an invoice against the details of a purchase order. After an order is placed, the goods are shipped, and the invoice is received, all three documents are compared to ensure accuracy. The material/part numbers, prices, quantities, and descriptions are included to do it. Each producer uses a different scoring system based on these factors. For certain sellers, the description may be of the utmost significance, while the material/part number may be the determining factor for others. Some other suppliers may prioritize quantity, cost, etc. Having a pricing barrier is a standard business practice adopted by most businesses. It can handle various situations, including tax value differences, handling fees, and price changes. Invoices, purchase orders (POs) and other documentation upon delivery must all be consulted for more information. It could be time-consuming for some businesses because of the huge supplier bills that include pages of line-item data.

Therefore, these criteria should be taken into account by the line item matching algorithm. The absence of training data further hinders the development of this algorithm, limiting us to unsupervised procedures. In addition to numerical similarity, semantic similarity is the primary component of our approach. As detailed below, the method is divided into two parts. Using lexical normalization, the invoice line item string was normalized according to Han et al., (2010) [44]. Recognizing ill-formed Out of Vocabulary (OOV) terms is called lexical normalization. The proposed technique filters out terms not found in a standard dictionary. Use the fuzzy similarity score to determine how well the list of line items matches the PO. The TF-IDF vector of bi-grams and tri-grams represents each string in fuzzy matching, and the cosine similarity between any two strings is calculated.

A high score (more than 0.7) is returned when fuzzy matching is used to calculate a similarity score for the strings "Glycerine white distilled 12%" and "Vinegar white distilled 12%". It is due to the many bi-grams that match between the two strings. As a result, we need to exclude such string pair combinations from the subsequent comparison. We chunk noun phrases using the Python Spacy 4 Application Programming Interface. If there is a mismatch between the query string and the pool of strings for any noun phrases, those strings are removed from consideration for use in the comparison.

The next step is calculating an overall score based on cost, amount, and similarity. This is accomplished by comparing the costs and amounts shown on the invoices with those listed on the purchase order. There is a maximum permissible deviation that the accounting specialist has established. A higher score is awarded to the items if the values are within the range.

2.8. Accounting Codes Prediction

A general ledger account, a revenue center, and an expense center are just a few of the accounting codes that must be assigned to every service transaction to record and classify the cash outlay correctly. When an invoice is based on a PO, the accounting codes and approvals are handled during the PO preparation process. In contrast, the accounts payable team must seek business review and permission before they amend the accounting codes associated with a non-PO invoice. The accounting particulars are current according to the cost category outlined in the statement. The fact that this is a judging process means that the team will often err, and they are very reliant on the input of other business teams. As a result, automating this procedure helps to input the relevant accounting codes and decreases the dependent on the company. Identification of accounting codes depends on the line-item description and the specifics of the shipping process. There is a possibility that the description of the item ordered and the description included on the invoice will not be the same. As a result, we try to locate older invoices with reports and shipping data comparable to those found in more current ones.

The method is comparable to the one used to identify tax codes, which was disclosed in our earlier work [45]. This method may be used for the prediction of accounting codes and coders and reviewers. We conducted research and experiments for these predictions using various algorithms, such as random forest, logistic regression, support vector machine (SVM), and others. On the other hand, we found that a hybrid classifier, which combines a semantic similarity engine with a rule-based system, achieved the highest levels of accuracy, precision, and recall [36]. Data mining for semantically similar item descriptions is the primary goal of the Semantic Similarity Engine. Currently, this is done with the assistance of an information retrieval system due to the nature of line-item descriptions; however, any other semantic similarity engine can be used. Then, using these candidate-matching descriptions, a search is conducted in the past data to gather anything that fits these descriptions. Identical matches are rewarded more highly than comparable ones. The retrieved linked lines are sorted by the Rule-Based Engine based on the ship-to and -from addresses and business codes. Then, the results are arranged in descending order by time, giving more weight to the more recent entries in the set. The projected accounting code is then decided by a majority vote of the best N findings, where N is a configurable quantity that relies on empirical evidence and SMEs' knowledge. This determines the ultimate confidence score Cp, often known as.

$$Cp = Ds \times Wd + Ms \times Wm \tag{1}$$

where Ds represents similarity scores for a description and 0 Ds = 1 for an exact match, and by design Ds for fuzzy matches would be lower than for precise matches in a given configuration. Here represents the configurable weight that indicates the significance of line-item descriptions and Wm represents the possible weight assigned to the majority score.

However, the majority voting score (Ms) is evaluated as follows:

$$Ms = \frac{Nm}{N} \times \frac{Nm}{NT} \tag{2}$$

N is the quantity of selected data samples that are being considered for classification. Out of the candidate samples that were shortlisted, Nm represents the number of items for which the most common accounting code applies. The value NT indicates the many unique accounting codes in the N data samples.

2.9. Coder/Reviewer Forecasting

The "goods receipt" step is included in an invoice based on a purchase order. During this step, the receiver of the goods or services confirms that they have been received. On the other hand, you cannot do this with a non-PO invoice. As a result, it is necessary to provide the invoice to the concerned individual or department to confirm the delivery of the products or services. The invoice will include the name and mobile number of the purchaser, as well as the purchasing department's code or cost center. This is not always the case, however. The Accounts Payable team must use this data to identify the approver for each invoice.

On the contrary, not all invoices will have this information, and even if they do, it is not guaranteed to be correct. The group may need to consult various sources to determine a person's identity. This research takes on this challenge from a variety of angles, including the following:

(i) If identifying information is available, the system will use fuzzy search to find the person or department most comparable to the information supplied.
(ii) To fill in the blanks when necessary, the proposed work employs an approach similar to that employed to forecast accounting codes. This method uses an IR-based system that looks at the line-item description to find the people or departments that have recently gotten the goods or services again.

2.10. Tax Code Prediction

In this phase, you will give the appropriate tax code to each item on the invoice. This step may rely on one or more criteria, such as the item description, item quantity, and price, location from where the item was sent, location to which the item will be transported, vendor details, and the moment of the purchase. A semantic similarity engine looks for line-item descriptions in previous data similar to other reports in the database to identify tax codes. After that, a search is performed using these potential matching descriptions in the previous data to collect all line items with these descriptions. Hereafter, sorting is performed by the vendor's presence and filtered by the shipping address and business code. The findings are then arranged in chronological order to address the possibility that the relevant provisions of the tax law may have evolved, preventing any notion drift that may have occurred. After then, a prediction of the tax code is made based on the majority vote of the top N results. The method is comparable to identifying tax codes detailed in our earlier study [41]. The anticipated confidence (Cp) in this case is determined by the following, which is comparable to the accounting code prediction:

$$Cp = Ds * Wd + Ms * Wm + Vs * Wv + Tm * W \quad (3)$$

where the total weights for the various components, $Wd + Wv + Wt + Wm = 1$, In this case, Wt represents the weight (importance) given to the tax rate indicated on the invoice, if one is present. It should be noted that different tax codes may be linked to the same tax percentage. If the predicted tax code matches one of the tax codes linked to the tax percentage, Tm is 1; otherwise, it is -1. Vendor details are identified by the letters Vs and Wv, respectively. Wv stands for the configurable weight assigned to vendor details. Figure 2 shows the prediction ledger with reduction status.

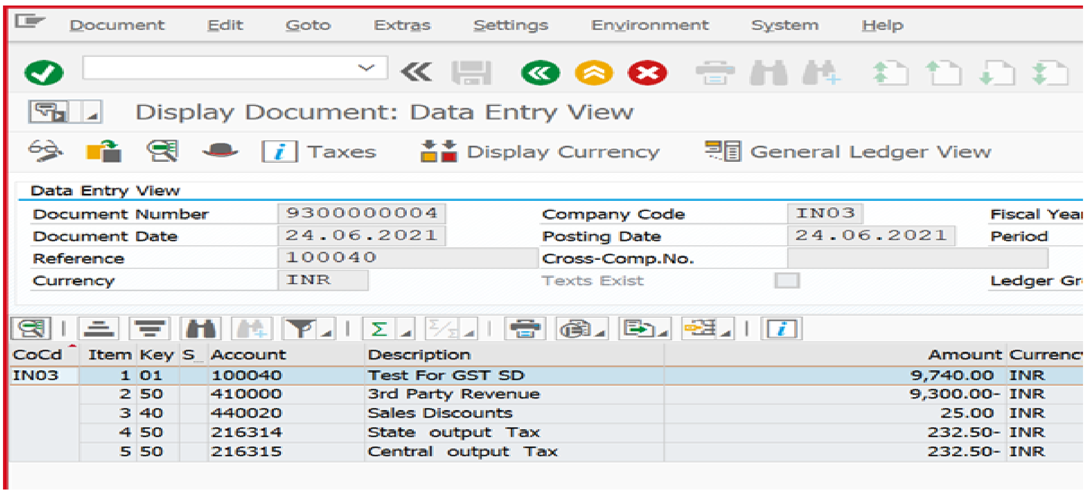

Figure 2. Prediction ledger with reduction status.

2.11. Drawing through Experience

Two confidence thresholds determine the weight of each item: (i) minimal confidence (*Cmin*) and (ii) maximum confidence (*Cmax*). These thresholds are used in the four AI modules discussed above line-item matching, coder prediction, accounting codes prediction, and tax codes prediction. The aforementioned artificial intelligence applications include these thresholds (*Cmax*). If the confidence level is higher than *Cmax*, the forecast is validated as accurate, and the step is completed automatically without human participation. The line item for that module will be made available for human review and discussion if the predicted confidence (Cp) is between the thresholds set by the C*max* and C*min*. After that, the agent can express support for the forecast if it seems proper to them, or they can express support for the prediction if they think it's wrong. After collecting this input, an attempt is made to enhance the underlying model. If the anticipated confidence is lower than the minimum defined threshold, denoted by the expression "*Cp Cmin*," the invoice is sent back into the workflow so that it may be manually processed. Each time the system is rolled out to a new client, great care is taken to determine the appropriate confidence levels (*Cmax* and *Cmin*). This means that *Cmax* is set to an enormous number while *Cmin* is set to a negligible one. This time is called the "hyper-care phase," and the agents confirm all of the predictions for a few weeks. The data gathered from the agents is then examined, and the standards are adjusted as necessary to keep the accuracy high while keeping the amount of human labor to a minimum.

Reducing *Cmax* would lead to an increase in the number of auto-posted invoices. In the Line-item matching method, the two hyper-parameters are used that, when adjusted depending on user input, cause an adjustment to be made to the overall confidence score. The hyper-parameters are modified in such a manner that, in the case of positive feedback, the learning rate is very sluggish, and in the case of negative feedback, the learning rate is relatively rapid. These hyperparameters guarantee that our algorithm correctly identifies matches by providing adequate positive and negative input. Similarly, the confidence of a projected class is altered every time a prediction receives an upvote (meaning agreement) or a downvote (meaning disagreement). It is the case when identifying tax codes or accounting codes. The education module includes this new data point. The model is built to consider the agreement between agents regarding the feedback. The simplest form of the feedback mechanism gives the system the ability to learn and remember information independently and the capacity to prevent data drift and concept drift.

3. Results and Discussion

Two accounts have the intended system in place; one is a significant international electronics distributor, and the other is a global retailer. These accounts have a combined annual volume of 80,000 invoices to be processed through the system. The system has been rolled out to these customers in Europe and North America; however, there are plans to expand its availability to additional markets in Asia, Europe, and Latin America. At this time, it has processed seventy thousand invoices for the electronic distributors' clients, delivering an efficiency of seventy-six percent (transactions that required either no or minimal human intervention). Only 7555 invoices, less than 11 percent of the total, require complete manual processing. This number includes 6631 invoices that are duplicates. This indicates that 62,154 invoices, or more than 88 percent of total invoices, were managed through the proposed system. The system still runs in hyper-care mode, where an agent checks each invoice, even after processing 10,000 bills for the other client. These deployments have been so successful that the system is being rolled out to an additional 37 markets worldwide for these two clients.

Tax rates may need to be applied, and it may be necessary to verify, match, and process the items on an invoice. The expected annual volume for the markets in which the system is already operational is 88 thousand invoices, and each invoice may contain multiple items. After indexing the document, it takes a human agent approximately ten minutes to manually process one invoice before it can be posted to ERP. Since 80,000 invoices have been handled, even a low estimate of a three-minute save for each invoice means that 4000 h of labor have been spared. Considering the annual volume of 800 thousand invoices, the savings are anticipated to amount to 40,000 person-hours annually after the system has been deployed to additional markets and is operational, [15,31]. Both these researchers noted that it is anticipated that this reduction in time will become significantly more significant once customers develop a greater comfort level with and trust in the AI capabilities. Langmann and Kokina's (2021) study also found the same line of the functionality of AP in terms of automating the entire invoicing process to save critical work hours and also to fully utilize the functional capabilities of AI/ML-powered automated AP process to channel the manual invoicing process to more digitized one.

Because several touchpoints are involved in processing bills, each handled by a separate agent, there is a significant wait time when invoices are sent between various agents. With this technology's aid, we reduced the cycle time between receiving an invoice and publishing it by at least 90%, automating the process and obviating human involvement. Additionally, our technology can discriminate between identical invoices. The system has successfully identified duplicate invoices with a total value of over 25 million dollars. This result accords with previously established findings [42]. Tater et al., [45,46] study developed an AI-driven system that processed ~80 k invoices; out of that, 76% of invoices were handled and processed automatically with no human interventions. The above research has also successfully detected the double payments error that often comes with the man-made handling of invoices.

As more invoices are processed, the system's artificial intelligence modules are built to learn new abilities and get better with the help of agent input. Since of this, the confidence criteria would be able to be appropriately updated, and a more significant number of invoices would be automatically posted without any interaction from a human being because the confidence forecasts would be higher. As was already noted, one of our biggest problems is making our system generalizable, reusable, and scalable for new customers. The modular and flexible architecture lets us quickly set up the system for a new customer with the fewest changes and work. We can drag and drop different parts to make them work together. Despite this challenge, we have been successful in overcoming it. Now that it has shown its superiority over the manual approach, it is in the early deployment stage for three other customers.

The research [43] investigates the use of machine learning and decision support systems in the invoicing process and highlights these tools' advantages and disadvantages. It also demonstrates that there is a wide range of variation in how various businesses view cost centers and accounts and that the complexity of invoicing changes depending on the parameters used [47]. In their research on the subject, Desai et al., (2021) [37] underline the significance of automation and Robotic Process Automation (RPA) in the processing of invoices. Machine learning algorithms can determine Invoice payment status in several ways. The authors mention research into creating invoices, including the similarities between purchase order line items and invoice line items. Yujian and Bo (2007) [41] also explain how tax codes are assigned, specifically, how we use a methodology that considers historical data for classification. Other drift forms, such as data and concept drift, have also been examined in earlier research.

In addition, Tater et al., (2021) [45] explain the process of determining tax codes by following a method in which the previous data for tax code classification is considered. Data drift and concept drift are two types discussed in previous studies, such as the one by Mourya et al., (2020) [42]. The RPA, rule-based solutions, and electronic invoicing platforms are some examples of the kinds of solutions that are being utilized by other businesses today. The main issue with these systems is that their main applications deal with organized data or repetitive operations. Routine actions that require minimal mental effort on the user's part might benefit from RPA. Rule-based solutions would once again apply to a defined set of rules.

Additionally, not every business generates enough invoices to warrant having its electronic invoicing systems. For these platforms to work, web apps must be built that enable suppliers to enter their invoices in a particular format before the invoice can be processed. Instead, the proposed solution employs machine learning techniques to deal with complex tasks and is designed to interact with unstructured data like line item descriptions.

4. Conclusions

Automating managing accounts payable requires developing a flexible system where individual modules can be used or disregarded. Some modules include line-item matching, coder name prediction, accounting code prediction, and tax. Some code prediction methods are supervised, others are unsupervised, and others are rule-based. The input agents are helpful for several of these modules, especially the ones that boost performance. This aids in addressing the problem of hidden data and data alterations and drifts. These agent comments also contribute to fine-tuning the confidence criteria, which enables a more significant number of invoices to be automatically posted without any interaction from a human being over time. In addition, since the system was developed using a modular architecture, each module may be independently modified or upgraded according to the data characteristics, client needs or in place of an algorithm that performs more effectively. The system is effectively deployed for two clients across different countries, and we are now doing so for other customers and markets while making minor adjustments. This demonstrates both the generalizability and the scalability of the system that has been suggested. Clients can do superior vendor relationship analysis with the assistance of comprehensive logging and the data acquired by the system. To be ready for the work that will be done in the future, we need to consider ways that customers may independently add new rules or modules to the system if a particular requirement arises. Due to audits and restrictions, some new customers are afraid to adopt such methods. Thus, the industry has to solve this issue. Future work will be directed to adopt the leverages of newly developed large language models to automate the process and reduce computational and manual manpower burdens.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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