Dynamic generation of Decision Model and Notation rules for tax regulations – case study from Swiss accounting offices

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Abstract

This study investigates the integration of Decision Model and Notation (DMN) with generative artificial intelligence (AI) to support the dynamic and explainable automation of decision-making processes in the domain of tax-related accounting. Addressing a recognized gap in the literature, we propose and empirically validate a hybrid human-AI framework for decision rule generation, implemented within LUCA - an enterprise-grade system deployed across Swiss accounting offices. The system leverages BPMN-driven workflows, AI-supported document understanding, and DMN-based rule management to formalize tacit expert knowledge. The methodology is grounded in a descriptive case study approach, utilizing participant observation and iterative validation. Key findings indicate a substantial improvement in automation efficiency, enhanced auditability, and effective rule reuse across distributed organizational units. We demonstrate that combining generative AI with DMN enables scalable, high-fidelity decision modeling while preserving transparency and human oversight. The study contributes a replicable model of knowledge acquisition and governance for data- and regulation-intensive environments.

Keywords: decision model and notation (DMN), generative AI, decision automation, accounting systems, explainable artificial intelligence, business process management, knowledge formalization, hybrid human-AI systems.

1. Introduction

This paper addresses the challenge of formalizing and scaling expert decision-making in tax-related invoice accounting through automation. As artificial intelligence (AI) and automation reshape the accounting profession-streamlining routine tasks and enhancing data analysis-the authors propose a structured method for dynamically generating decision rules using the Decision Model and Notation (DMN) standard combined with generative AI. The goal is to explore how this synergy improves the efficiency, transparency, and scalability of accounting processes.

Recent studies highlight that AI and automation are now key forces transforming accounting-"streamlining routine tasks, supporting data analysis, and reshaping the roles and responsibilities of accountants" [4, p. 1]. Technologies with the greatest impact include AI, big data, blockchain, and cloud accounting [22]. Others also emphasize machine learning (ML), chatbots, and robotic process automation (RPA) as drivers of change [1].

This study contributes: (1) a hybrid human–AI framework for decision rule creation, (2) a feedback-driven approach to expanding explainable models, and (3) a business model for knowledge sharing across federated environments. It shows how DMN can translate tacit expert knowledge into scalable, auditable decision logic.

Automating cost document accounting requires identifying, classifying, and assigning attributes like tax rates or accounts-decisions traditionally made by accountants based on their expertise. This raises a core question: how far can such decisions be automated?

While DMN enables the clear definition of business rules and integrates well with BPMS workflow engines, the creation and maintenance of decision logic remain challenges [8]. Furthermore, practical applications of DMN in accounting are still underreported, which motivates this research.

Two research questions guide the study:

RQ1*: How can DMN be systematically applied to improve and enhance accounting processes through formalization and reuse of knowledge?*

RQ2: *How can generative AI be effectively integrated into DMN to dynamically generate decision rules, and what resources and techniques support this process?*

To answer these, the paper presents a case study of Swiss accounting offices using a DMN-based model to automate decision-making. This model also serves as a growing knowledge base, expanded with each iteration. A complementary business model enables rule sharing across offices serving SMEs.

The paper is structured as follows: Section 2 reviews DMN's background and applications. Section 3 outlines the case study method. Section 4 presents the context and organization. Section 5 describes the automated process, rule development, and the technical-business model. The final discussion addresses the research questions and future applications of DMN-AI integration.

2. Related works

2.1. Business rule modeling tools

The modeling of decision rules has long been central to software engineering. In the 1970s and 1980s, E. Yordon introduced tools like decision trees, tables, structured English, and pseudocode to formalize user requirements at the analysis stage [21]. These tools helped analysts define logic for developers, but lacked direct automation capabilities.

A later step was the Semantics of Business Vocabulary and Business Rules (SBVR) by OMG, first released in 2008 [14]. SBVR offered a formal, multilingual vocabulary to define business terms and rules [15], but it was not designed for executable decision logic in IT systems.

The rise of workflow and BPMS systems renewed interest in decision automation. While BPMN became the de facto standard for modeling processes [12], it struggled with complex decisions involving multiple conditional branches, which hindered model clarity [7]. Embedding decision logic in code (e.g., IF-THEN-ELSE structures) made processes opaque and hard to manage for business users.

This led to a need for tools enabling both human-readable decision modeling and executable logic for BPMS engines. Earlier rule engines and proprietary business rule systems attempted this but lacked openness and scalability. As Freund and Rücker noted, these limitations are now being overcome by standardized tools like DMN, which they predict will gain widespread adoption [8, p. 150].

2.2. DMN basis and applications

The Decision Model and Notation (DMN) standard, developed by the OMG, was first released in 2015, with its latest version (1.5) published in 2024 [13]. DMN provides a modeling language for defining business decisions and rules in a form that is both human-readable and machine-executable. DMN consists of two main tools: (1) a graphical decision requirements diagram (DRD), which models the structure and data dependencies of decisions, and (2) an expression language, FEEL (Friendly Enough Expression Language), for encoding logic [13]. Decision tables in DMN are structured with rules in rows and conditions/results in columns, enhanced with features like hit policies and completeness indicators. FEEL enables precise, executable rule logic using formal syntax, data types, and logical expressions. DMN rules are executed via rule engines in BPMS, typically triggered by business rule tasks in BPMN processes. The standard targets operational decisions and supports partial or full process automation.

Research on DMN includes validation of its correctness and semantics [3], concerns about understandability and explainability in complex domains [5], and integration patterns with BPMN [2],[6],[11]. Applications span domains such as IoT [10], blockchain [9], public services [18], and medicine [19]. However, documented uses of DMN in finance, accounting, or auditing remain rare, despite the relevance of constructs like decision tables and BPMN in accounting information systems (AIS) [17].

3. Research method

In this paper, we applied a qualitative, descriptive case study approach to investigate the use of DMN in the LUCA system for automated invoice accounting. As outlined by Yin [20], this method is suited to answering "how" questions about current phenomena beyond the researcher's control. A key strength of this approach is the use of multiple data sources, which enhances data credibility [16]. The authors participated directly in system design and implementation. Data were collected via participant observation, internal documentation, and iterative feedback. Validity threats - such as potential bias and the lack of formal interviews - were addressed through transparent reporting and rule performance cross-validation. The results of the work should serve as inspirations for those companies that implement business process automation (BPA) to use the described technology in their projects.

4. Case study

4.1. Characteristics of project and its environment

Switzerland's 26 cantons, each with distinct tax laws and accounting requirements, create a fragmented regulatory environment that complicates financial document automation for SMEs. This legal and linguistic heterogeneity (German, Italian, French, English) presents significant challenges to standardizing and scaling accounting systems. With over 600,000 SMEs and more than 4,000 accounting offices, there is strong demand for automation solutions.

Founded in 2020, Robotic Ledger AG developed software for automating expense classification and posting, targeting SMEs and accounting firms. Initially a local application, it evolved into a Python-based web app, and later into a solution built on the Camunda BPM platform with integrated DMN and BPM standards. BeOne, a Polish firm, led the platform configuration. The system - named LUCA after the 15th-century accounting pioneer - was launched in 2023 and is now used by several Swiss offices. The software continues to grow, informed by ongoing input from its accounting users.

5. Undertaken actions

5.1. Automatic invoice classification and posting process – step by step

To accurately capture accountant decision-making, the process was decomposed and formalized using the DMN standard. Figure 1 presents the complete flow; the main components are described below.

Figure 1. Invoice classification and posting process.

Document classification and content understanding

The process is implemented in executable BPMN within the Camunda platform (Fig. 2). It starts with uploading and standardizing a document, followed by OCR and classification using word embeddings. DMN rules handle ambiguities - e.g., prioritizing keywords or resolving conflicts in classification. In low-confidence or uncertain cases, user input is recorded into decision tables for future learning.

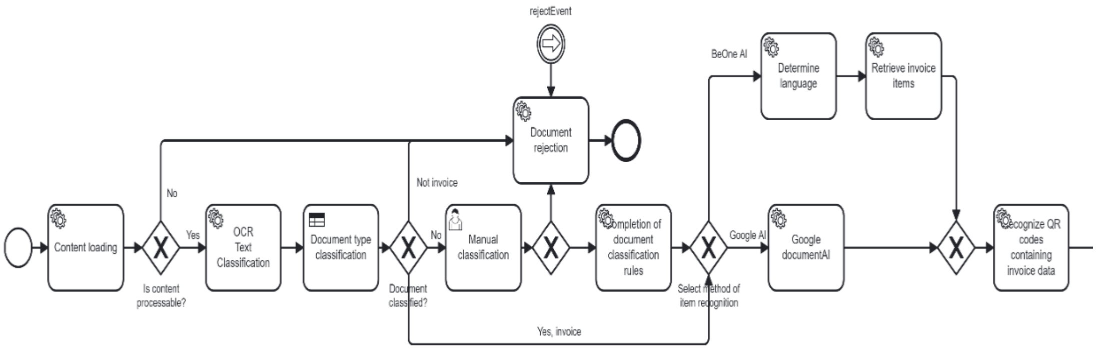

Figure 2. Document and content classification and recognition – Executable BPMN.

After classification, invoice content is interpreted. Line items are extracted using AI tools (e.g., BeOne AI, Google Document AI), QR codes are scanned (commonly present in Swiss invoices), and payment indicators are identified through keyword analysis

Vendor verification, product, and tax assignment

Once content is recognized, the system identifies and verifies the vendor. Verification is shared across the platform: once confirmed by one office, it applies to others. The system also checks for duplicates and validates payment methods based on vendor-specific rules.

The core of the process involves mapping line items to products. When no match is found, manual input is triggered. Based on issuer and product context, the system suggests product groups for cost classification. If needed, accountants define new groups. Verified items are used to create posting lines, with tax rates assigned through DMN based on posting groups (Fig. 3)

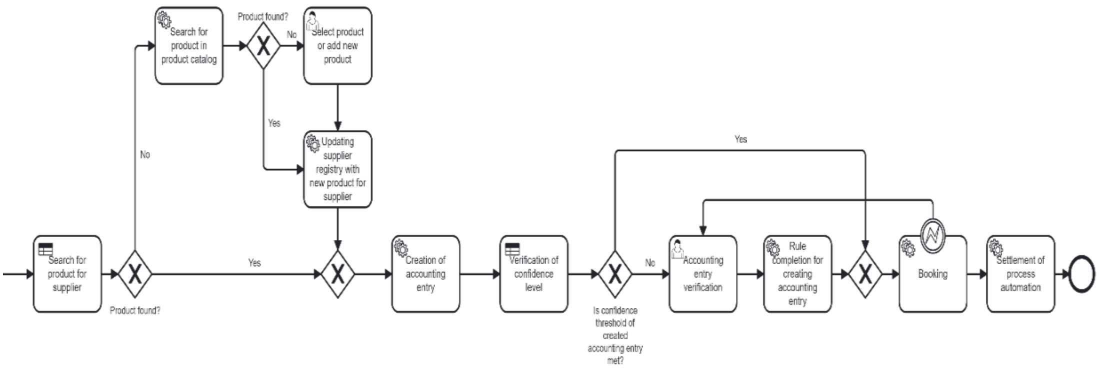

Figure 3. Creation of accounting entries and settlement of process automation – Executable BPMN.

Invoice posting

Depending on the confidence score, invoices may be routed for manual review. During this stage, key attributes are verified, and decision data is collected to refine rules. Before final posting, the system confirms the correct accounting period and fiscal year. Once verified, the entry is posted to the accounting system.

At the end, the system calculates the automation rate for the instance, which informs client billing and continuous process optimization - explored further in the Innovative Business Model section.

5.2. Storing and sharing accounting knowledge model based on decision tables

The automation process described in the previous section is underpinned by a structured network of decision tables, each encapsulating explicit rules for the classification and parametrization of recognized invoice elements. These tables collectively drive the execution flow, guiding the process through successive stages until final posting. In the BPMN diagrams (Figures 2 and 3), each Business Rule Task (visually marked with a table icon) invokes a corresponding DMN table, ensuring consistent execution of encoded expert logic.

The sequential use of decision tables mirrors the cognitive model of an experienced accountant interpreting cost documents. The overall decision structure is illustrated in the DMN

Decision Requirements Diagram (Figure 4), which captures the logical dependencies between low-level document attributes (e.g., issuer name, invoice line description) and high-level financial classifications (e.g., general ledger accounts, tax codes).

To reflect and formalize expert reasoning, the model was constructed using a multi-layered rule abstraction technique. At the lowest level, atomic decisions determine product identification. Subsequent tables derive intermediate categorizations (e.g., product groups, accounting groups), culminating in the allocation of tax rates and financial entries. Each decision is traceable, auditable, and explainable - a core advantage of DMN's transparent logic formalism.

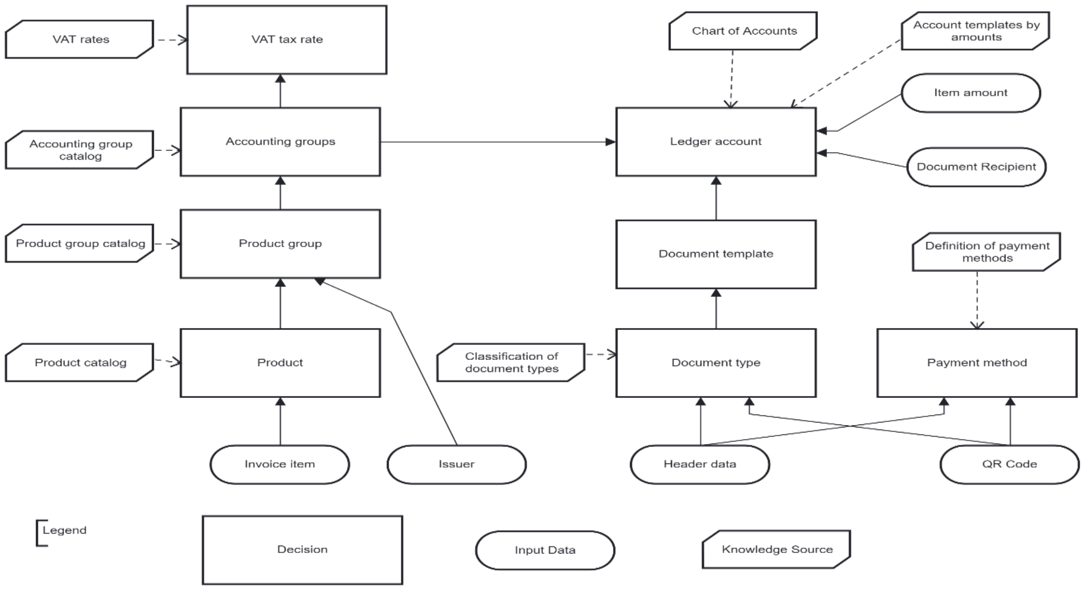

Figure 4. Decision model structure – DRD.

This model decomposes the decision-making process typically performed by an accounting assistant and introduces a structured mechanism for augmenting it with data obtained through manual interventions. Specifically, during the stage of product identification based on invoice item descriptions, the system autonomously attempts to match the appropriate product category using regular expressions embedded within predefined decision rules.

In cases where the system fails to classify an invoice item automatically, a semi-automated rule-learning workflow is triggered. This process leverages the capabilities of Large Language Models (LLMs) to support two primary tasks:

- categorical inference: The LLM determines the most appropriate product category based on the semantic content of the item description. For example, it may be prompted with: "*Which category best fits '{invoice item description}'? Choose one: Smartphone, Computer, Office Equipment*",
- pattern induction: The LLM generates candidate regular expression patterns that generalize across similar item descriptions. These expressions are based on templated prompts, such as: "*Generate a regular expression pattern for a {product group} that matches: {invoice item description}*".

For example, if the invoice line contains the description 'Apple iPhone', the system dynamically inserts this into the prompt. The LLM may then return a rule that is ready to be inserted into the decision table such as:

Invoice item description (input)	**Product group (output)**
`matches("\b(Apple\s)?iPhone\s\d{1,2}(\s(Pro|Pro Max|Mini|Plus))?(\s\d+(GB|TB))?\b”)`	Smartphone

This regular expression captures a wide range of expected variants - such as Apple iPhone 14 Pro 256GB or iPhone 13 Mini - while also identifying limitations due to typographical errors or semantic ambiguity (e.g., iPhonex 14 Pro, Apple SmartPhone 14).

To enhance transparency and user engagement, a human-in-the-loop validation cycle is applied:

- the user reviews suggested matches and non-matches,
- if necessary, the regular expression is edited or approved,
- once confirmed, the rule is inserted into the decision table with a low-confidence label.

This rule is then subject to incremental trust calibration. Each time the rule is triggered during live processing, a confirmation task is generated. Upon three successful human confirmations, the rule is promoted to trusted status and executed autonomously thereafter.

This AI-augmented rule refinement mechanism supports adaptive knowledge modeling. Unlike static expert systems, LUCA evolves dynamically based on real-world feedback and human validation. This approach draws inspiration from active learning frameworks in machine learning, where model accuracy improves through selective user input.

Moreover, by embedding the learning process within standard DMN tables, the system ensures that all rule modifications remain explainable and compatible with business governance standards. This method applies not only to product classification, but also to other decision tables (e.g., tax rate determination or payment method validation), ensuring broad applicability and scalability.

By combining symbolic decision logic with generative AI capabilities, the LUCA system bridges the gap between formal knowledge representation and practical decision support in dynamic, regulation-intensive domains like accounting.

5.3. Innovative technical and business model of accounting services – sharing knowledge

The LUCA project introduces a business model in which clients upload expense documents via the Bexio platform-one of the leading tools for SMEs in Switzerland. Uploaded invoices are automatically retrieved and processed by LUCA, triggering a flow in which DMN decision tables assign accounting parameters such as tax rates or accounts. This enables full automation of classification and posting. When existing rules are insufficient, the task is forwarded to an accountant, whose input is recorded and later incorporated into the decision model after reaching a defined confidence level.

Over time, LUCA evolves into a growing knowledge base for accounting decisions, continuously improved by each processed document. The learning process accelerates through collaborative use: as more accounting offices participate, rule coverage expands faster via shared insights. To support multi-tenant collaboration, LUCA provides fine-grained access control, allowing offices to designate decision rules as private or shared. This ensures sensitive logic remains isolated while reusable rules propagate across tenants.

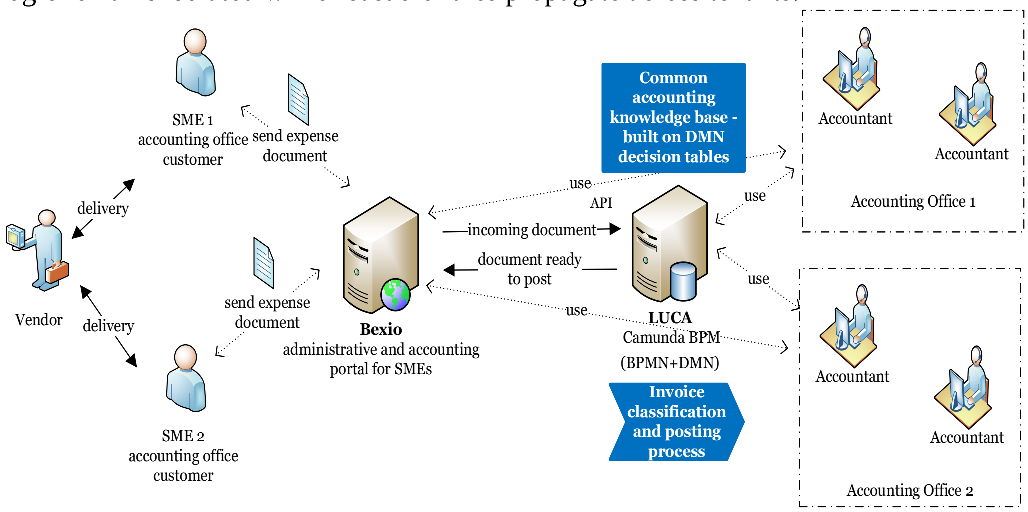

Figure 5. LUCA The architecture and flows of this business model.

Additionally, LUCA employs an incentive-aligned billing model: clients are charged only for automated tasks, while manual interventions enhance future automation. This approach supports ongoing system improvement and offers immediate value to all parties. The result is a "win–win–win" model: clients benefit from efficiency, accounting offices reduce operational costs, and LUCA developers gain a stronger, smarter platform with each use.

6. Evaluation

The evaluation of the LUCA system was conducted through a field implementation across several Swiss accounting offices. The goal was to assess the effectiveness of the proposed DMN-based automation framework using both quantitative performance metrics and qualitative indicators of system usability and auditability. The evaluation methodology drew upon instrumentation and analytical capabilities offered by the Camunda BPM engine, which served as the execution and monitoring backbone of the solution.

From a quantitative standpoint, process performance was systematically measured using Camunda's History Service API, which enables the collection of granular event logs and execution metrics. The evaluation encompassed key indicators such as:

- automation rate, measured by the share of invoice items processed without manual intervention,
- processing time, measured as the duration from invoice ingestion to completion of posting decisions,
- rule reuse rate, assessed through analysis of DMN decision instance logs.

The results showed an average automation rate of 74%, indicating that a substantial portion of accounting classifications could be handled autonomously via predefined or dynamically generated rules. Furthermore, the mean processing time per invoice decreased from over 4 minutes (manual baseline) to 1.5 minutes post-deployment. This improvement was statistically validated across multiple process instances and attributed to the elimination of manual classification tasks and reduction in cognitive load, supported by Camunda's parallel evaluation of DMN decision tables.

In terms of model effectiveness and maintainability, Camunda's decision history tracking allowed for the systematic evaluation of how often existing DMN rules matched new input cases. An increasing trend in rule reuse over time was observed, suggesting that the DMN knowledge base evolved toward generalization and operational stability. The system also benefitted from Camunda's ability to version and audit individual decisions, enabling longitudinal analysis of rule adaptation without loss of traceability.

Qualitative evaluation was performed via structured feedback sessions with end-users (accounting professionals), combined with the analysis of decision path transparency using Camunda Cockpit and Optimize. Participants emphasized the value of:

- decision explainability, facilitated by the visual inspection of decision tables and input-output mappings,
- auditability, supported by comprehensive logging of input data, rule conditions, and resulting outputs for each transaction,
- error analysis, enabled by drill-down inspection of failed or exceptional cases.

Finally, the system's scalability and adaptability were assessed by deploying LUCA in heterogeneous operational contexts, ranging from small accounting teams to distributed office networks. Camunda's modular architecture, support for external decision services, and integration with heterogeneous data sources allowed for rapid adaptation without altering the underlying process logic.

In sum, the evaluation methodology-rooted in instrumented observation, empirical measurement, and user validation-confirms the practical utility of DMN-based decision automation in the accounting domain. Moreover, it illustrates how BPM platforms such as Camunda can serve not only as workflow engines but also as research instruments for capturing, validating, and evolving complex decision logic in dynamic environments.

7. Discussion

This study contributes to the literature by presenting a novel integration of generative AI and Decision Model and Notation (DMN) for the dynamic generation of decision rules in accounting automation. Empirical results demonstrate that this approach enhances operational efficiency, transparency, and accuracy in document-based decision-making processes. From a theoretical perspective, it provides structured insight into the synergy between AI-driven rule generation and DMN-based decision management, offering valuable implications for future automation frameworks.

A key methodological advancement lies in the feedback-driven extension of decision tables. In the LUCA system, process gaps triggered by novel document types or products are identified and resolved through human-in-the-loop interventions. These decisions are retained, verified, and incorporated into the system's evolving rule base. By enabling distributed knowledge acquisition, the system facilitates a federated learning approach among multiple accounting offices, accelerating adaptation to emerging scenarios.

A notable observation concerns the usability of DMN for non-technical users. The tabular structure of DMN decision tables was perceived as intuitive and comparable to spreadsheet tools familiar to accountants. This accessibility supports transparency and verifiability of automated decision-making processes.

From a technical perspective, DMN exhibited high scalability, successfully handling datasets with up to one million rules while maintaining acceptable processing performance. This makes it a suitable tool for large-scale automation scenarios requiring explainable and auditable logic.

Two key conclusions were drawn regarding RQ2 on the integration of AI and DMN. First, AI and DMN are not mutually exclusive but complementary. AI supports initial document classification and assists in rule generation, while DMN ensures rule traceability and governance. Second, in terms of execution speed, DMN significantly outperforms AI models in real-time processing tasks. Hence, a hybrid strategy - where AI contributes to rule formation and DMN governs decision execution - emerges as optimal.

The LUCA project also exemplified an innovative business model in which automation performance directly influences pricing. Clients are billed based on the proportion of decisions executed automatically, incentivizing continual system refinement. This outcome-based model democratizes access to automation for SMEs while ensuring measurable value delivery.

8. Conclusion

This study confirms the applicability and effectiveness of DMN in the automation of structured accounting processes. DMN's graphical decision modeling and rule-based logic enable domain experts to participate directly in automation design, fostering interdisciplinary collaboration. The integration of AI components further enhances the decision model by enabling continuous learning without compromising interpretability.

The explainability of DMN strengthens user trust in automation systems, which is critical in regulated domains such as accounting. Unlike opaque AI models, DMN structures provide clear justifications for decisions, enhancing compliance and transparency.

We foresee DMN playing a central role in the digital transformation of finance and management, particularly in domains requiring rule-based but adaptable decision logic - such as dynamic pricing, inventory control, and risk assessment. Future research will focus on evaluating DMN performance across sectors and exploring its integration with advanced AI models to further extend the boundaries of explainable automation.

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References

1. Bavaresco, R., Nesi, L., Barosa, J., Antunes, R., Righi, R., Costa, C., Vanzin, M., Dornelles, D., Junior, S., Gatti, C., Ferreira, M., Silva, E., and Moreira, C.: Machine learning-based automation of accounting services: An exploratory case study. International Journal of Accounting Information Systems Vol. 49. (2023)
2. Bazhenova, E., Zerbato, F., Oliboni, B. and Weske, M.: From BPMN process models to DMN decision models. Information Systems Vol. 83, pp. 69-88. (2019)
3. Calvanese, D., Dumas, M., Laurson, U., Maggi, F., Montali M., and Teinemaa, I.: Semantics and Analysis of DMN Decision Tables in Business Process Management.

Lecture Notes in Computer Science, Vol. 9850. Springer, Cham. (2016)

4. Chukwuani, V.:The Transformational Impact of Automation and Artificial Intelligence on the Accounting Profession. International Journal of Accounting and Financial RiskManagement, 5(1), pp. 1-8. (2024)
5. Corea, C., Kampik, T. and Montali, M.: Explainable DMN. Lecture Notes in Business Information Processing, Vol. 526., Springer, Cham. pp. 55-72. (2024)
6. de Leoni, M., Felli, P. and Montali, M.: Integrating BPMN and DMN: Modeling and Analysis. Journal on Data Semantics Vol. 10, pp. 165-188, (2021)
7. Dumas, M., La Rosa, M., Mendling J. and Reijers, H.: Fundamentals of Business Process Management. Springer, Berlin. (2018)
8. Freund, J., Rücker, B.: Real-Life BPMN. Using BPMN and DMN to analyze, improve, and automate processes in your company. 4th edition. Jakob Freund and Bernd Rücker. (2019)
9. Haarmann, S., Batoulis, K., Nikaj, A. and Weske, M.: DMN Decision Execution on the Ethereum Blockchain. In: Advanced Information Systems Engineering. CAiSE 2018. Lecture Notes in Computer Science Vol. 10816, Springer, Cham. pp. 327-341. (2018)
10. Hasić, F., Serral, E. and Snoeck, M.: Comparing BPMN to BPMN + DMN for IoT process modelling: a case-based inquiry. In: Proceedings of the 35th Annual ACM Symposium on Applied Computing (SAC '20), New York. (2020)
11. Janssens, L., Bazhenova, E., De Smedt, J., Vanthienen, J. and Denecker, M.: Consistent Integration of Decision (DMN) and Process (BPMN) Models. CAiSE forum Vol. 1612, pp. 121-128. (2016)
12. OMG: About The Business Process Model and Notation Specification version 2.0. (2011), https://www.omg.org/spec/BPMN/2.0/About-BPMN/. Accessed January 10, 2025
13. OMG: Decision Model and Notation. Version 1.5. (2024), https://www.omg.org/spec/DMN/1.5. Accessed January 20, 2025
14. OMG: Semantics Of Business Vocabulary And Rules. Version 1.0. (2008), https://www.omg.org/spec/SBVR/1.0. Accessed January 10, 2025
15. OMG: Semantics Of Business Vocabulary And Rules. Version 1.5. (2019), https://www.omg.org/spec/SBVR/1.5. Accessed January 10, 2025
16. Patton, M.: Qualitative evaluation and research methods (2nd ed.). Sage, Newbury Park. (1990)
17. Richardson, V., Chang J. and Smith, R.: Accounting information systems 3rd edition, McGraw-Hill, (2021)
18. Tavantzis, T., Promikyridis, R. and Tambouris, E.: Towards exploiting BPMN and DMN in public service modeling. In: Proceedings of the 27th Pan-Hellenic Conference on Progress in Computing and Informatics (PCI '23), New York. (2024)
19. Wiemuth, M., Junger, M., Leitritz, M., Neumann, J., Neumuth, T. and Burgert, O.: Application fields for the new Object Management Group (OMG) Standards Case Management Model and Notation (CMMN) and Decision Management Notation (DMN) in the perioperative field. International Journal of Computer Assisted Radiology and Surgery Vol. 12. pp. 1439-1449. (2017)
20. Yin, R.: Case Study Research and Applications 6th Edition. Thousand Oaks: Sage Publication, (2018)
21. Yourdon, E.: Modern Structured Analysis. Prentice Hall, New York. (1988)
22. Zhang, Z., Xiong, F., Xie, X., Fan. X. and Gu, Y.: The Impact of Artificial Intelligence and Blockchain on the Accounting Profession. IEEE Access, vol. 8, pp. 110461-110477. (2020)