The Demonstration of Generative AI in the Development of Process Architecture: The Case of Bank Deposits

Mohammad Sabri
Department of Software Engineering
School of Information Technology
Zarqa University, Jordan
msabri@zu.edu.jo

Ahmad Samhan
Department of Software Engineering
School of Information Technology
Zarqa University, Jordan
Ahmad.Samhan@zu.edu.jo

Ghassan Samara
Department of Computer Science, School of Information Technology
Zarqa University, Jordan
gsamara@zu.edu.jo

Sami Abuezhayeh
Department of Computer Science and Creative Technologies, The University of the West of England, UK
sami.abuezhayeh@uwe.ac.uk

Mahmoud Odeh
Department of Cybersecurity
School of Information Technology
Zarqa University, Jordan
modeh@zu.edu.jo

Sulieman Mohammad
Department of Electronic Marketing and Social Media, Zarqa University, Jordan
Faculty of Business and Communications
INTI International University, Malaysia
dr_sliman73@aabu.edu.jo

Abstract: *Business Process Architecture (BPA) provides a holistic, portfolio-centric view of organizational processes; however, a key challenge in its development particularly within the Riva methodology lies in the manual identification of Units of Work (UOW) from Essential Business Entities (EBEs). This task is typically performed through expert workshops and subjective interpretation of Riva filters, making it time-consuming, difficult to scale, and prone to inconsistency across practitioners. To address this limitation, this study investigates the use of Generative Artificial Intelligence (GAI) to support and partially automate UOW identification and architectural modeling. The paper focuses on Riva step three (classification of EBEs into UOWs) and step four (derivation of UOW relationships and diagrams), evaluating two Large Language Models (LLMs) ChatGPT and DeepSeek against expert-validated results from a real-world banking deposits case study. Quantitative analysis shows strong alignment with expert classifications, where DeepSeek achieved perfect precision, recall, and F1-score, while ChatGPT demonstrated near-perfect performance. Beyond classification accuracy, both models successfully generated UOW diagrams, exhibiting complementary strengths in lifecycle rigor and functional reasoning. As a primary contribution, this work introduces GAIRivaClassifier, a semi-automated algorithm that operationalizes Riva filters, lifecycle detection, and heuristic reasoning to support systematic UOW identification and diagram generation. The findings provide empirical evidence that GAI can effectively augment design-time BPA activities, enabling hybrid human-Artificial Intelligent (AI) collaboration for more consistent, scalable, and adaptive Riva-oriented Process Architecture (PA) development.*

Keywords: *Business process architecture, Riva method, GAI, ChatGPT, DeepSeek, process modelling, large language models.*

Received September 29, 2025; accepted February 09, 2026
https://doi.org/10.34028/iajit/23/4/5

1. Introduction

Business Process Architecture (BPA) provides a holistic, portfolio-oriented representation of how organizational work is structured and coordinated. By focusing on stable process structures rather than isolated workflows, BPA supports strategic alignment, integration across business units, and long-term organizational adaptability. Among systematic BPA methodologies, the Riva method is widely regarded as a rigorous, object-oriented approach that derives Process Architectures (PAs) from Essential Business Entities (EBEs) and their lifecycles.

Despite its conceptual strength, the practical application of Riva presents notable challenges. In particular, Riva step three extracting Units of Work (UOWs) from EBEs represents a critical bottleneck in BPA development. This step requires the application of multiple conceptual filters, such as lifecycle existence, organizational ownership, role exclusion, and dependency analysis. In practice, UOW identification is typically performed through expert workshops and iterative discussions, making it time-consuming, difficult to scale, and highly dependent on subjective interpretation. As a result, different practitioners may derive divergent PAs from the same domain, limiting repeatability and consistency.

Recent advances in Artificial Intelligence (AI), and especially Generative Artificial Intelligence (GAI) based on Large Language Models (LLMs), have opened new opportunities for supporting Business Process Management (BPM). Prior research has demonstrated the potential of LLMs in BPM tasks such as process discovery, process improvement ideation, and operational analysis [14, 15]. These studies primarily emphasize runtime optimization, execution support, and analytical augmentation, highlighting the strengths of LLMs in reasoning over process data and textual descriptions.

However, the design-time phase of BPA-particularly architectural blueprinting and systematic process derivation-remains largely underexplored in AI-based BPM research. Existing work provides limited empirical evidence on how GAI can support formal BPA methodologies or operationalize their underlying principles. This gap is especially pronounced in the context of the Riva method, where UOW identification requires disciplined application of filters and lifecycle logic rather than purely descriptive reasoning. Consequently, there is a lack of structured approaches that leverage GAI to support Riva-oriented BPA modeling while maintaining methodological rigor and explainability.

To address this gap, this study investigates the use of GAI as a design-time assistant for BPA development within the Riva methodology. Focusing on Riva step three (UOW identification) and step four (derivation of UOW relationships and diagrams), the study evaluates two LLM-based tools-ChatGPT and DeepSeek-using a validated banking deposits case study. The outputs produced by the GAI tools are systematically compared against expert-validated results to assess classification accuracy, adherence to Riva filters, and consistency of reasoning. Furthermore, the study introduces a semi-automated mechanism to formalize the UOW identification process and reduce reliance on purely manual interpretation.

The contributions of this paper are summarized as follows:

- Identification and analysis of Riva step three as a methodological bottleneck, highlighting the limitations of manual UOW classification in terms of scalability, consistency, and effort.
- An empirical evaluation of GAI for UOW classification, comparing ChatGPT and DeepSeek against expert-validated ground truth within a real-world banking case study.
- The proposal of the GAIRivaClassifier algorithm, which operationalizes Riva filters, lifecycle detection, and heuristic reasoning to support semi-automated UOW identification.
- Demonstration of GAI-assisted Riva step four, showing how LLMs can support the generation and refinement of UOW diagrams as part of BPA design.
- Insights into hybrid human-AI collaboration for BPA development, outlining how expert oversight and AI reasoning can be combined to improve repeatability and design efficiency.

The remainder of this paper is organized as follows. Section 2 reviews background concepts related to GAI, BPM, and the Riva methodology. Section 3 describes the research methodology, including the case study, prompt design, and evaluation criteria. Section 4 presents the experimental results and quantitative analysis of UOW classification. Section 5 introduces the GAIRivaClassifier algorithm and demonstrates its application. Section 6 discusses the findings, limitations, and implications for BPA modeling. Finally, section 7 concludes the paper and outlines directions for future research.

2. Generative AI and Machine Learning

GAI ushers in a new generation of computational approaches, where machines learn from historical datasets and utilize these insights to solve new problems. It automates the process of creating decision-making frameworks, helps humans perform better, and brings out hidden patterns in large data stores [7]. GAI is a type of Machine Learning (ML) that focuses on creating new examples that look and behave like the data it was trained on. ML is often used for things like classification, regression, or reinforcement learning. GAI, on the other hand, often uses unsupervised or self-supervised learning. That makes it good at creating many types of content, like text, images, and other data [6].

A GAI system is usually built in layers. It has a main model, data processes, and extra layers that handle how results are shown and shared. Because of this setup, GAI can be used in many fields. For example, it can write website content, generate code, or help solve real-world problems. When it runs on a strong system, GAI can speed up new ideas, learn and adapt in different ways, and drive big changes across many sectors [1].

3. Generative AI Applications and Challenges

GAI is a type of ML that uses neural networks to create new content. This can be text, sound, or images that look like they were made by people. Examples include tools like ChatGPT, DALL-E 2, and DeepSeek. These platforms can hold conversations, make content, and design creative outputs in many areas such as education, business, and healthcare [6]. In the education field, it motivates adaptable learning environments, customizes learning and teaching practices and materials, and improves student participation. The GAI also benefits the business sector in terms of virtual customer support, automated marketing ideas or ad campaigns, and human resource management tasks. Similarly, GAI positioned correctly can help in medicine, health awareness, and guidance, or telemedicine services.

GAI can create new things, and it opens doors to new applications, but it also brings a number of substantial problems and other important restrictions, such as technical, environmental, and ethical challenges. A prime example of something problematic is hallucination, which refers to the generation of wrong responses or made-up facts [4]. Making content with AI creates a problem for schools and research. It raises questions about whether the work students and researchers submit is really their own [2]. AI systems can also copy human bias, since the data they are trained on may already contain unfair patterns [12]. There is also an environmental issue. Training large models uses a lot of power, which leads to high carbon emissions [13]. Because of this, new methods are needed. AI outputs should be checked, bias reduced, and GAI designed in more sustainable ways. Only then can it be safe to use across different fields.

4. Process Architecture Modelling and Riva Method

In recent years, BPA has been used not only in business but also in other areas. It is now applied in fields like cloud computing and organizational change management. In these cases, BPA helps by modeling changes in a clear way, which makes systems more flexible and transparent [9, 10, 11]. The long-lasting nature of the BPA is attributed to its simplicity, universality, and versatility as an integration framework for modelling and analysis of a wide range of workplace practices.

Empirical studies distinguish between two main approaches to PAs [5]. The first methodology adopts a service-oriented viewpoint, while the second is predicated on decomposition, which encompasses pipeline, divisional, and hierarchical frameworks. Nonetheless, these methodologies are frequently perceived as lacking systematic rigor, as they do not adhere to standardized protocols or consistent methodologies for the development of PAs across various organizations. In contrast, systematic methodologies prioritize the derivation of processes and their interconnections from clearly articulated principles. In this context, five distinct modeling strategies have been delineated: goal-oriented, function-oriented, object-oriented, action-oriented, and reference model-oriented architectures [3].

Among systematic methodologies, the Riva approach [8] is esteemed as a comprehensive and object-oriented paradigm for the development of BPA. This method initiates with the identification of EBEs the critical components that define the fundamental operations of an organization and subsequently proceeds to the systematic derivation of UOWs along with their dynamic interrelationships. Ould [8] highlighted that organizations operating within analogous business domains frequently converge towards comparable Riva-oriented architectures, thereby accentuating the method's generalizability and consistency across various domains.

The Riva methodology is classified among the BPA methodologies that adhere to the object-oriented paradigm [8]. Ould [8] posits Riva as a lucid, pragmatic, and systematic methodology for formulating PAs that are derived from the EBEs, asserting that the Riva-based PA exhibits remarkable similarity across organizations operating within the same business domain. EBEs represent critical entities that encapsulate the essence of business, rendering them essential. The Riva methodology facilitates the development of BPA through a series of structured steps. These steps are enumerated as follows:

- Define the domain and business scope.
- Identify and refine Candidate EBEs (CEBEs) into finalized EBEs.
- Extract the UOWs.
- Determine dynamic relationships among UOWs and develop a UOW diagram.
- Convert the UOWs diagram into an initial or first cut PA.
- Refine the first cut into the second PA.

5. Methodological Approach

This study adopts an experimental and data analysis approach to evaluate the effectiveness of using GAI in PA. ChatGPT and DeepSeek are utilized in a crucial step in the Riva method, which is step three, extracting the UOWs from EBEs. A UOW is a key EBE that has a specific lifetime and is managed and tracked throughout that period. Classifying EBEs into UOWs requires specific filters in order to determine UOWs. These filters were provided to GAI technologies before asking them to classify a specific dataset of EBEs into UOWs and non-UOWs. The dataset of EBEs was already collected and validated in a previous study and presents the EBEs of the deposits department in a bank in Jordan [9]. The GAI outputs are compared with the expert-validated UOWs of the deposits department using a quantitative approach.

5.1. Generative AI Configuration and Prompting Protocol

Two GAI tools based on LLMs were used in this study: ChatGPT (GPT-4-class model available at the time of experimentation via the OpenAI web interface) and DeepSeek (latest publicly available DeepSeek model accessed through its official web interface). Both models were accessed through their graphical user interfaces rather than Application Programming Interfaces (APIs).

Default generation settings provided by the platforms were employed for all experiments. These settings correspond to a low-temperature, low-randomness configuration (approximately temperature ≈0.2-0.3 with default top-p values), favoring deterministic and rule-consistent responses. As direct control of random seeds was not available through the web interfaces, each EBE classification was repeated three times per model. The final classification decision for each EBE was determined using majority voting across runs to mitigate stochastic variation.

A uniform prompt template was used for all experiments and for both models to ensure consistency and comparability. EBEs were provided to the models one at a time, rather than in bulk, to avoid contextual interference. Each prompt included:

1) A concise definition of a UOW according to the Riva methodology.
2) The four Riva filters used to exclude non-UOWs.
3) A single EBE to be classified. The models were instructed to return a binary decision (UOW/non-UOW) together with a brief justification indicating the applied filter or reasoning.

This interaction protocol ensured controlled prompting, reduced response variability, and enabled a fair comparison between the evaluated GAI tools.

5.2. Evaluation Metrics and Scoring Criteria

The performance of the GAI models was evaluated using a binary classification framework, where each EBE was classified as either a UOW or a non-UOW. Expert-validated classifications from the case study were used as ground truth.

For each model, a confusion matrix was constructed comprising True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). A TP represents an EBE correctly classified as a UOW, while a TN corresponds to an EBE correctly identified as non-UOW. FPs and FN denote incorrect UOW and non-UOW classifications, respectively.

Based on the confusion matrix, standard evaluation metrics were computed, including accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified EBEs. Precision reflects the proportion of EBEs classified as UOWs that are correct, while recall indicates the proportion of actual UOWs correctly identified by the model. The F1-score represents the harmonic mean of precision and recall, providing a balanced measure of classification performance.

In addition to binary correctness, the quality of the model's justification was evaluated separately. Binary performance metrics were computed solely on the final UOW/non-UOW label, independent of the accompanying explanation. Explanatory quality was assessed qualitatively using a three-level rubric:

- **R0:** Incorrect classification
- **R1:** Correct classification with incomplete or weak reasoning.
- **R2:** Correct classification with appropriate application of Riva filters and coherent justification.

This secondary assessment supports interpretability analysis but does not influence quantitative performance scores.

6. Demonstration of the Riva Method on Bank Deposits Using Generative AI

Development of PA using the Riva method requires the application of the Riva steps and filters on a case study. In this paper, these steps and their filters were already implemented in the case of the deposit departments of a bank in Jordan. In addition, the output elements of the PA were validated. By presenting this PA and its elements as a benchmark, the GAI can be utilized to execute Riva step three, which is investigated and compared with a reference.

The adoption of GAI in Riva step three 'extracting the UOWs' requires an overview of the application of previous steps and presenting the EBEs that GAI technologies are going to classify into UOWs using the nominated filters. These steps are as follows:

- Step one: the deposits department that operates in the banking and financial services domain.
- Step two: in this step, candidate EBEs are brainstormed using suggested prompt questions and filtered into EBEs with Riva step one filters. This step is critical in carrying on the remaining Riva steps and was automated using knowledge management enablers and semantic ontologies with Semantic Web Rule Language (SWRL) rules [9]. By demonstrating this step to the deposits department of a bank, the following list of EBEs was extracted and validated by the domain experts (see Table 1). In this table, the EBEs are provided with a method for classifying these EBEs into UOWs using brackets. The nomination of UOWs is a core step that involves applying specific filters through brainstorming and meeting efforts, as discussed in the next step.

Table 1. List of bank deposits EBEs with bracketed UOWs.

1. Automated Teller Machine (ATM)	25. Bank manager
2. Account	26. Corporate
3. Account form	27. Deposit services request
4. Accounts executive	28. Current account
5. Bank statement	29. Customer Information File (CIF)
6. Bills Payment	30. Customer verification
7. Blacklisted people	31.Customer relationship officer
8. Bank Policy	32.Deposits
9. Cash and teller services request	33. E-card
10. Cash deposit	34. Fixed account
11. Cash withdrawal	35. Joint account
12. Central bank regulations	36. Money transfer
13. Central bank	37. Retail
14. Cheque	38. Safe box deposit
15. Cheque book ordering	39. Safe box form
16. Cheque cashing	40. Salary transfer
17. Cheque clearing	41. Saving account
18. Cheque deposit	42. SMEs
19. Currency Exchange	43. Local bank
20. Foreign bank	44. Teller
21. Bank branch	45. Banking system
22. Bank customer	46. Sharia restrictions
23. Central bank regulatory requirements	47. Cash
24.Currency	48. Internet banking

- Step three: this step determines the qualified EBEs that are UOWs and excludes those that are not. A

UOW is an EBE with a defined lifetime that requires monitoring. Additional filters are applied to narrow down EBEs to only those that are UOWs by excluding:

- Filter 1: EBEs that cannot be UOWs (e.g., cancer prevention-it has no lifetime to manage).
- Filter 2: EBEs that are UOWs for other organizations but not in our own (e.g., data protection acts-relevant to a quality management Group but not a bank).
- Filter 3: EBEs that are only roles in processes (e.g., bank teller a role, not a UOW)
- Filter 4: EBEs that are Part of another EBE and do not have their own lifetime (e.g., safe box form-depends on safe box deposit).

6.1. Application of GAI Technologies on Riva Step Three

Based on previous Riva step three filters, GAI technologies, including ChatGPT and DeepSeek, were provided by these filters to classify EBEs into UOWs. Both applications were requested to answer whether an EBE is a UOW supported by reason or the filter applied. Results in Table 2 show that the classified EBE is in UOW with the correct sign.

Table 2. Classification of EBEs into UOWs with GAI technologies.

No.	EBE	ChatGPT classification at UOW	DeepSeek classification as UOW	Filter No/ChatGpt reasoning	Filter No/DeepSeek reasoning
1	ATM	✕	✕	(3)/A resource/ tool, not an EBE with its own lifetime	(3)/Physical device, not a managed lifecycle
2	Account	✓	✓	Has a lifecycle (opened, maintained, closed) valid UOW	Has a lifecycle (opening, transactions, closing)
3	Account form	✕	✕	(4)/Part of Account-no independent lifetime	(4)/Part of “account opening” UOW
4	Accounts executive	✕	✕	(3)/A role in the process, not an EBE	(3)/Role, not a managed entity
5	Bank statement	✕	✓	(4)/Output of account activity-not a standalone UOW	Generated, stored, and managed over time
6	Bills payment	✓	✓	A recurring service with its own handling and tracking	A transactional process with a lifecycle
7	Blacklisted people	✕	✓	(2)/Reference data; used for control, not a UOW	Managed list (added/removed over time)
8	Bank policy	✕	✕	(2)/Control or guideline-not tracked or “looked after”	(2)/Governance rule, not a managed process
9	Cash and teller services request	✓	✓	UOW-customer requests that initiate a workflow with a lifetime	A service request with a lifecycle
10	Cash deposit	✓	✓	UOW-transaction with lifecycle from initiation to completion	A transactional process (initiated→completed)
11	Cash withdrawal	✓	✓	UOW-handled and tracked with accountability	A transactional process (initiated→completed)
12	Central bank regulations	✕	✕	(2)/External control-not a UOW for the bank	(2)/External compliance, not managed by the bank
13	Central bank	✕	✕	(3)/A role/external entity, not a UOW	(3)/External entity, not a process
14	Cheque	✓	✓	Treated individually, processed through the lifecycle (issued, cleared, archived)	Managed lifecycle (issued→cleared→archived)
15	Cheque book ordering	✓	✓	UOW-customer request that has a lifecycle	A request process (order→fulfillment)
16	Cheque cashing	✓	✓	UOW-specific, trackable process	A transactional process (presentation→payment)
17	Cheque clearing	✓	✓	UOW-complete process with responsibility and resolution	A back-office process with defined steps
18	Cheque deposit	✓	✓	UOW-similar to a cash deposit	A transactional process (deposit→processing)
19	Currency exchange	✓	✓	UOW-request-driven process	A service with a defined process
20	Foreign bank	✕	✕	(3)/External entity, not an EBE, the bank looks after	(3)/External entity, not a process
21	Bank branch	✕	✕	(3)/Physical or organizational structure, not UOW	(3)/Physical location, not a process
22	Bank customer	✓	✓	Considered a UOW-managed through onboarding, service, and closure	Managed lifecycle (onboarding→servicing→offboarding)
23	Central bank regulatory requirements	✕	✕	(2)/External controls, not internally owned UOWs	(2)/External compliance, not managed by the bank
24	Currency	✕	✕	(4)/Part of another UOW (e.g., exchange, cash handling)	(1)/Physical medium, no lifecycle
25	Bank manager	✕	✕	(3)/A role	(3)/Role, not a managed entity
26	Corporate	✕	✕	(4)/Descriptive label-no standalone lifetime	(3)/Customer segment, not a process
27	Deposit services request	✓	✓	UOW-service workflow initiated by the customer	A service request with a lifecycle
28	Current account	✓	✓	UOW-similar to account	Account type with a lifecycle
29	CIF	✓	✓	UOW-created, updated, and deleted with lifecycle	Managed record (created→updated→archived)

30	Customer verification	✓	✓	UOW-specific process with defined start and end	A process (e.g., KYC checks)
31	Customer relationship officer	✕	✕	(3)/A role	(3)/Role, not a process
32	Deposits	✓	✓	General UOW category	A core banking process
33	E-card	✓	✓	Issued, managed, renewed-has a lifecycle	Managed lifecycle (issuance→usage→cancellation)
34	Fixed account	✓	✓	UOW-lifecycle includes setup, maturity, closure	Account type with a lifecycle
35	Joint account	✓	✓	UOW-same as account, with shared access considerations	Account type with a lifecycle
36	Money transfer	✓	✓	UOW-traceable process	A transactional process
37	Retail	✕	✕	(4)/Descriptor/category-not a standalone UOW	(3)/Customer segment, not a process
38	Safe box deposit	✓	✓	UOW-involves customer registration, access control, and termination	A service with a lifecycle (rental→access→closure)
39	Safe box form	✕	✕	(4)/Part of the process-no independent lifecycle	(4)/Part of “safe box deposit” UOW
40	Salary transfer	✓	✓	UOW-involves authorization, execution, and confirmation	A bulk payment process
41	Saving account	✓	✓	UOW-tracked and maintained	Account type with a lifecycle
42	SMEs	✕	✕	(4)/Organizational descriptor-not UOW	(3)/Customer segment, not a process
43	Local bank	✕	✕	(3)/External entity-not managed by this bank	(3)/External entity, not a process
44	Teller	✕	✕	(3)/A role	(3)/Role, not a process
45	Banking system	✕	✕	(3) A system/tool, not an entity with a lifecycle	(3)/IT infrastructure, not a process
46	Sharia restrictions	✕	✕	(2)/Rules/controls not-looked after	(2)/Compliance rule, not a process
47	Cash	✕	✕	(4)/A resource-used in UOWs like deposit/withdrawal	(1)/Physical medium, no lifecycle
48	Internet banking	✓	✓	UOW-service platform that’s initiated, maintained, and closed per customer	A digital service with user lifecycle management

6.2. Case Study Scope and Limitations

This study is based on a single real-world case study involving the deposits department of a Jordanian bank. The selected case provides a validated and well-documented set of EBEs and expert-confirmed UOWs, making it suitable for controlled experimentation and comparison of GAI outputs against established ground truth.

While a single-case design is appropriate for evaluating the feasibility and internal validity of the proposed approach, it introduces limitations regarding external generalizability. The results may reflect domain-specific characteristics of the banking sector, organizational practices, and regulatory context. In addition, the evaluation was conducted using English-language EBEs and textual prompts, which may not capture multilingual or multimodal challenges present in other organizational environments.

Accordingly, the findings should be interpreted as an empirical demonstration of applicability rather than a claim of universal performance across industries. Future research is required to validate the proposed approach across multiple domains, organizations, and linguistic contexts, and to assess its robustness under varying PAs and organizational settings.

6.3. Results: GAI-Driven Classification of EBEs into UOWs

According to previous tables, both GAI technologies show significant alignment with expert-validated EBEs classification into UOWs (see Table 1), with slight variations in results. DeepSeek achieved 100% agreement with 27 identified UOWs. ChatGPT closely matched DeepSeek performance, agreeing on 25 of the 27 UOWs (89% accuracy), excluding ‘Bank Statement’ and ‘blacklisted people’ UOWs.

Dataset Characteristics and Statistical Validity

The evaluation dataset consists of 48 EBEs derived from the deposits department case study. Based on expert validation, 27 EBEs were classified as UOWs, while 21 EBEs were classified as non-UOWs, yielding a moderately balanced class distribution (56.25% UOWs and 43.75% non-UOWs).

To contextualize the reported performance results, confidence intervals were considered for the primary evaluation metrics. Given the limited dataset size, the reported accuracy, precision, recall, and F1-score should be interpreted as dataset-specific estimates rather than population-level guarantees.

Since both ChatGPT and DeepSeek were evaluated on the same set of EBEs, their classification outcomes are paired. To assess whether the observed performance difference between the two models is statistically significant, a McNemar test was applied to the paired predictions. The test focuses on EBEs for which the two models disagreed. Given the small number of discordant cases, the test did not indicate a statistically significant difference at conventional confidence levels, suggesting that both models perform comparably on this dataset.

Both GAI technologies used nearly the same Riva filters to classify EBEs, examining features such as tracking over time, job roles, and dependency on other items. They agreed most of the time-about 83% of cases, indicating they share a similar understanding of guidelines. The slight differences are related to factors such as the clarity of the start-to-finish lifecycle and how items are actually used in business. DeepSeek was stricter on lifecycle criteria, and ChatGPT considered the functional context more.

Beyond accuracy, a statistical evaluation was conducted to assess the performance of DeepSeek and ChatGPT in classifying EBEs into UOWs. Based on expert-validated classifications, precision, recall, and F1-score for both tools were computed. Precision represents the percentage of EBEs classified as UOWs by AI that were correct. Recall measures the percentage of UOWs correctly identified by the AI. The F1-score is the mean of precision and recall. Results indicate that DeepSeek achieved perfect performance across all metrics (precision=1.0, recall=1.0, F1=1.0). ChatGPT also achieves a high performance with slightly lower results (precision=0.96, recall=0.93, F1=0.94). These results emphasize the robustness of both tools.

6.4. An Algorithm for UOWs Classification

After the use of GAI in the classification of UOWs, a comprehensive algorithm was developed depending on GAI technologies to translate the steps followed to filter EBEs into UOWs.

Algorithm 1: GAIRivaClassifier Pseudocode.

```
Begin
Load pretrained knowledge base (role keywords, lifecycle
  verbs, external entities)
Initialize user-defined filters (roles, external entities,
  dependencies)
Initialize learned patterns (UOW templates, non-UOW
  templates)
Input EBE (Essential Business Entity)
if EBE is a Role then
    Decision ← Excluded (Filter 3: Role)
    goto End
end if
if EBE is an External Entity then
    Decision ← Excluded (Filter 2: External Entity)
    goto End
end if
if EBE is a Dependent Entity then
    Decision ← Excluded (Filter 4: Dependent Entity)
    goto End
end if
if lifecycle not detected then
    Decision ← Excluded (Filter 1: No lifecycle)
    goto End
end if
if EBE matches heuristics (account, transaction,
  request, service, deposit, transfer) then
    Decision ← UOW (confidence = 0.85)
else
    Decision ← Uncertain (confidence = 0.50)
end if
Record decision {status, reason, confidence}
if user feedback provided then
    Update learned patterns
end if
End
```

The above algorithm does the following steps:

- Loading pre-trained knowledge or generic business patterns.
- Prepare the Riva filters provided by the user.
- Classify EBEs by sequentially applying Riva filters (dependencies, roles, and lifecycles), checking lifecycles, and pre-trained fallback (in doubt or unclear, use general business logic).
- Learn based on feedback.

To further illustrate the operational logic of the proposed GAIRivaClassifier, a flowchart was developed to capture its decision-making process in a structured and visual form. The flowchart summarizes how an input EBE is systematically evaluated against the four Riva filters, lifecycle detection, and pre-trained heuristics before being classified as either a valid UOW, excluded entity, or uncertain case. By visualizing the filtering and classification stages, the diagram provides a clearer understanding of the sequential flow of conditions and outcomes, highlighting the algorithm's transparency, explainability, and capacity to integrate both rule-based and heuristic-driven reasoning. This visual representation also serves as a practical bridge between the detailed pseudocode and the conceptual description, making the algorithm more accessible to both researchers and practitioners, see Figure 1.

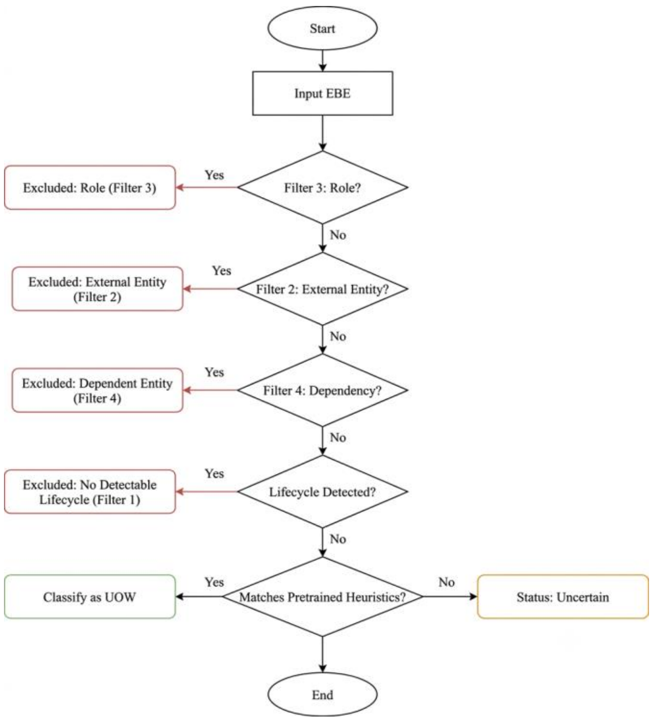

Figure 1. GAIRivaClassifier flowchart.

The flowchart complements the pseudocode by highlighting conditional paths and termination points, which directly inform the automation of Riva step three.

6.5. Application of GAI Technologies on Riva Step Four

After classifying UOWs using GAI technologies, the authors further investigated the application of GAI technologies in developing the UOWs diagram. A few requests were made to enhance UOW's diagram using both GAI technologies, specifically to address missing UOW items, font, shapes, etc. ChatGPT offered to show all possible logical relationships based on banking domain knowledge. The following diagrams were generated by both technologies (see Figures 2 and 3).

Figure 2. UOWs diagram generated by ChatGPT GAI.

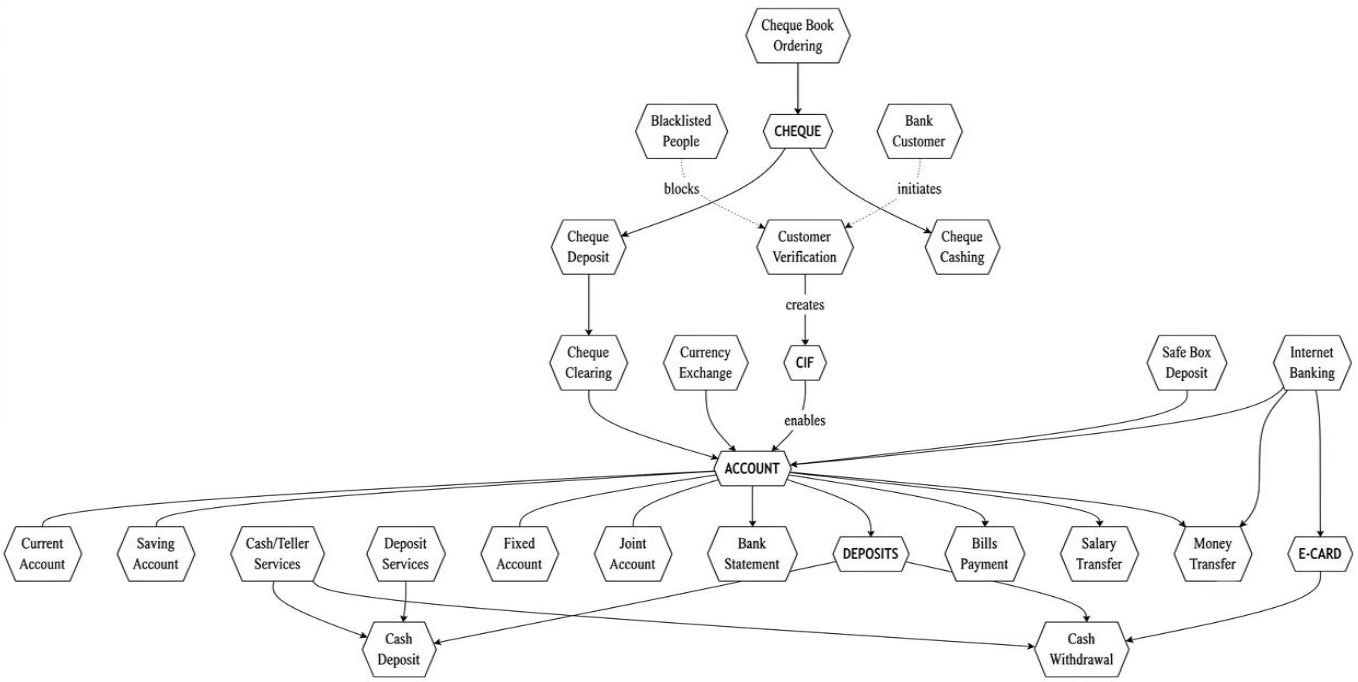

Figure 3. UOWs diagram generated by DeepSeek GAI.

7. Discussion

The study shows how GAI can be used in the Riva method for building BPA. A test between ChatGPT and DeepSeek showed that both have different strengths. DeepSeek followed lifecycle rules very closely and reached perfect scores in precision, recall, and F1. It was also better at staying within the set rules and explaining its reasoning. ChatGPT was more flexible and could adjust to different situations. This makes the two models useful in different ways.

The results suggest that GAI assistants can help with Business Process Automation (BPA) in many organizations. DeepSeek works better in fields like banking, healthcare, and public services, where strict rules must be followed. ChatGPT fits better in fast-changing areas that need flexible solutions. The study shows the value of combining humans and AI people handle rule checks, while AI supports flexible reasoning.

This study also looks at the design stage of PA. It builds on earlier work with LLMs in Business Process Management (BPM) [14, 15]. The GAIRivaClassifier algorithm is another step forward. It gives a partly automated way that uses Riva filters, lifecycle checks, and heuristics.

These results show that GAI can be used not only for analysis but also for planning and design in BPA. Still, there are some limits that need to be considered. The evaluation was restricted to a single case study in the banking deposits domain, which may limit the generalizability of results across industries. Moreover, the reliance on English prompts and text-based reasoning overlooks the multilingual and multimodal challenges faced in global organizations. Another limitation lies in the black-box nature of LLMs, which raises questions about explainability, bias, and sustainability that require ongoing attention.

Limitations and Scope of Findings

While the results demonstrate strong alignment between GAI outputs and expert-validated classifications, several limitations should be acknowledged. First, the evaluation is based on a single organizational case study within the banking deposits domain. Although this case provides a validated and controlled environment for experimentation, the observed performance may reflect domain-specific characteristics, regulatory constraints, and established business practices that do not necessarily generalize to other industries.

Second, the dataset size is relatively small and focused on a fixed set of EBEs. While this is appropriate for an exploratory and design-oriented study, it limits the statistical power of the evaluation and the ability to draw population-level conclusions. Consequently, reported performance metrics should be interpreted as indicative of feasibility and consistency within the studied context rather than evidence of universal superiority over alternative approaches.

Third, the study relies on text-based prompts and English-language descriptions of EBEs. This excludes multilingual, multimodal, or diagrammatic representations that are commonly encountered in real-world BPA initiatives. In addition, the use of web-based interfaces restricted fine-grained control over model parameters and internal randomness, despite mitigation through repeated runs and majority voting.

Finally, LLMs remain inherently opaque, raising concerns related to explainability, bias, and long-term reliability. Although the proposed GAIRivaClassifier improves transparency by formalizing decision logic, expert oversight remains essential to ensure methodological correctness and organizational relevance.

Looking forward, future research should validate the GAIRivaClassifier across multiple domains such as healthcare, logistics, and education, and should explore integration with process mining and Business Process Model and Notation (BPMN)-based platforms. Expanding the algorithm to incorporate semantic ontologies, knowledge graphs, and domain-specific datasets could further strengthen accuracy and explainability. Finally, studies on hybrid human-AI collaboration would help clarify how expert oversight and AI-driven reasoning can jointly enhance the scalability, trust, and sustainability of BPA modeling.

8. Conclusions

This study explored the integration of GAI into PA development, specifically on Riva method steps three and four: identifying UOWs and determining their relationships. DeepSeek and ChatGPT were applied to a validated banking case study and showed a significant enhancement in the efficiency and accuracy of BPA development. The results indicated that DeepSeek achieved a complete alignment with the expert-validated results, while ChatGPT results were nearly accurate with minor differences. Both tools also presented strong reasoning when applying Riva filters, showing the potential of LLMs to learn and simulate systematic modelling approaches. Furthermore, the introduction of the GAIRivaClassifier algorithm reinforces the contribution of this research by presenting a semi-automated mechanism to classify EBEs into UOWs. This leads the way for future research toward a fully automated BPA modeling through an AI framework.

Overall, this paper contributes to the growing relationship of PAs and AI by empirically demonstrating that GAI could be effective in Riva-based BPA development. Future research should focus on evaluation across multiple domains and integrating AI with different BPA modelling and existing BPM platforms. This work provides a fundamental step towards intelligent, adaptive, and sustainable PAs design.

References

[1] Azamfirei R., Kudchadkar S., and Fackler J., "Large Language Models and the Perils of their Hallucinations," *Critical Care*, vol. 27, no. 1, pp. 1-2, 2023. https://link.springer.com/article/10.1186/s13054-023-04393-x

[2] Cotton D., Cotton P., and Shipway J., "Chatting and Cheating: Ensuring Academic Integrity in the Era of ChatGPT," *Innovations in Education and Teaching International*, vol. 61, no. 2, pp. 228-239, 2024. https://doi.org/10.1080/14703297.2023.2190148

[3] Dijkman R., Vanderfeesten I., and Reijers H., "Business Process Architectures: Overview, Comparison, and Framework," *Enterprise Information Systems*, vol. 10, no. 2, pp. 129-158, 2016. https://doi.org/10.1080/17517575.2014.928951

[4] Feuerriegel S., Hartmann J., Janiesch C., and Zschech P., "Generative AI," *Business and Information Systems Engineering*, vol. 66, no. 1, pp. 111-126, 2024. https://link.springer.com/article/10.1007/s12599-023-00834-7

[5] Malinova M., Leopold H., and Mendling J., "An Empirical Investigation on the Design of Process Architectures," *in Proceedings of the 11th International Conference on Wirtschaftsinformatik*, Leipzig, pp. 1211-1197, 2013. https://wi2013.de/proceedings/WI2013%20-%20Track%208%20-%20Malinova.pdf

[6] Nah F., Zheng R., Cai J., Siau K., and Chen L., "Generative AI and ChatGPT: Applications, Challenges, and AI-Human Collaboration," *Journal of Information Technology Case and Application Research*, vol. 25, no. 3, pp. 277-304, 2023. https://www.tandfonline.com/doi/full/10.1080/15228053.2023.2233814

[7] Noy S. and Zhang W., "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence," *Science*, vol. 381, no. 6654, pp. 187-192, 2023. https://www.science.org/doi/10.1126/science.adh2586

[8] Ould M., *Business Process Management: A Rigorous Approach*, BCS, The Chartered Institute. 2005. https://books.google.bf/books?id=qK-d0AjuMmQC

[9] Sabri M., Odeh M., and Saad M., "Deriving Object-Based Business Process Architecture Using Knowledge Management Enablers," *The International Arab Journal of Information Technology*, vol. 16, no. 3A, pp. 577-586, 2019. https://www.iajit.org/portal/PDF/Special%20Issue%202019,%20No.%203A/18604.pdf

[10] Samhan A., AlHajHassan S., and Odeh M., "Adapting Riva to Support Case Strategy Processes and Enable Modeling a Generalized Business Process Architecture," *in Proceedings of the 22nd International Conference on Advanced Computer and Information Technology*, Muscat, pp. 1-6, 2021. https://doi.org/10.1109/ACIT53391.2021.9677140

[11] Samhan A., Odeh M., Kossmann M., and Tbakhi A., "Business Process Architecture-Driven Change Management Applied to a Cancer Care Organization in a Systems of Systems Context," *in Proceedings of the 1st International Conference on Cancer Care Informatics*, Amman, pp. 205-214, 2018. https://doi.org/10.1109/CANCERCARE.2018.8618170

[12] Schramowski P., Turan C., Andersen N., Rothkoof C., and Kersting K., "Large Pre-Trained Language Models Contain Human-Like Biases of What is Right and Wrong to Do," *Nature Machine Intelligence*, vol. 4, no. 3, pp. 258-268, 2022. https://www.nature.com/articles/s42256-022-00458-8

[13] Schwartz R., Dodge J., Smith N., and Etzioni O., "Green AI," *Communications of the ACM*, vol. 63, no. 12, pp. 54-63, 2020. https://doi.org/10.1145/3381831

[14] Van Dun C., Moder L., Kratsch W., and Roglinger M., "ProcessGAN: Supporting the Creation of Business Process Improvement Ideas Through Generative Machine Learning," *Decision Support Systems*, vol. 165, pp. 113880, 2023. https://doi.org/10.1016/j.dss.2022.113880

[15] Vidgof M., Bachhofner S., and Mendling J., "Large Language Models for Business Process Management: Opportunities and Challenges," *in Proceedings of the International Conference on Business Process Management*, Utrecht, pp. 107-123, 2023. https://doi.org/10.1007/978-3-031-41623-1_7

Mohammad Sabri is an Associate Professor who completed his PhD at the University of the West of England (UWE), UK. Dr. Mohammad currently serves as the vice dean of scientific research at Zarqa University. He has a demonstrated history of working in the Software Development Industry and is skilled in various research areas, including Knowledge Management, Business Process Architecture, Business Modelling and Ontologies.

Ahmad Samhan received the B.Sc. and M.Sc. degrees (Hons.) in Computer Information systems, and the Ph.D. degree in Software Engineering from the University of the West of England (UWE), U.K. He is currently an Assistant Professor in Software Engineering. His Ph.D. degree was about Developing a Semantically-Enriched and Business Process Architecture-Driven Change Management Framework in the Systems-of-Systems Context. He was a part of the Software Engineering Research Group (SERG), UWE, during his doctoral studies. His research interests include Configuration Management, Business Process Architecture, the Systems-of-Systems, and Knowledge-based Approaches and Ontologies.

Ghassan Samara is a Professor at the Faculty of Information Technology, Zarqa University, Jordan. He earned his Ph.D. in Computer Networks from University Sains Malaysia (USM) in 2012. His research spans Vehicular Ad-hoc Networks (VANETs), Wireless Sensor Networks (WSNs), Cybersecurity, Cryptography, Cloud and Fog Computing, and AI. He has developed Secure Routing Protocols, Lightweight Cryptography Schemes for IoT, and AI-driven solutions for Intrusion Detection, Phishing Defense, Sentiment Analysis, Medical Diagnosis, and Traffic Prediction in Smart Cities. His recent work emphasizes sustainable Cloud computing, AI-enabled Edge Intelligence, and Intelligent Transportation Systems, with applications in Accident Prevention, Congestion Management, and Electric Vehicle Charging. With more than 150 peer-reviewed publications in international journals, conferences, and book chapters, Professor Samara's scholarship bridges AI, Security, and Intelligent Networking, Contributing to Advancements in Cyber Defense, IoT Ecosystems, Healthcare Informatics, and Smart Mobility.

Sami Abuezhayeh is a Senior Lecturer in the Department of Computing at the University of the West of England (UWE Bristol), UK, and a Fellow of the Higher Education Academy (FHEA). He has extensive experience in higher education, both within and outside the UK. Abuezhayeh is a member of the Computer Science Research Centre within the College of Arts, Technology, and Environment at UWE. His research interests include Software Engineering, Information Systems, Enterprise Systems, and Machine Learning. He has supervised numerous undergraduate and postgraduate dissertations, as well as research group projects.

Mahmoud Odeh is an Associate Professor at Zarqa University. He completed his higher education and PhD at Reading and Coventry University, UK. Mahmoud holds more than 15 years' experience in both the practical and academic fields, with 56 international certificates in Servers, Computer Virtualization, Smart Machine Simulation, and Cloud Computing. The Rapid Evolution of Cloud Computing Technology inspires his current research, primarily focusing on the Implementation of Innovative Technology.

Sulieman Mohammad is a Professor of Business Management at Al al-Bayt University, Jordan (currently at Zarqa University, Jordan), with more than 17 years of teaching experience. He has published over 100 research papers in prestigious journals. He holds a PhD in Financial Management and an MCom from Rajasthan University, India, and a Bachelor's in Commerce from Yarmouk University, Jordan. His research interests focus on Supply Chain Management, Marketing, and Total Quality (TQ). His ORCID ID is orcid.org/0000-0001-6156-9063.