

Design of an intelligent agent for interpreting financial statements in microenterprises: a Design Science Research approach

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Abstract– *Microenterprises often struggle to interpret financial information from basic accounting reports, which limits managerial decision-making in contexts with low financial expertise. Although intelligent financial systems have advanced, many prioritize predictive analytics and computational complexity over interpretability and usability for small business users. To address this gap, this paper presents the design of an intelligent agent for financial statement interpretation in microenterprises, developed through a Design Science Research approach. The proposed artifact converts simplified financial data into interpretable and decision-oriented insights by integrating financial ratio analysis, rule-based reasoning, and contextual aggregation. Its design emphasizes transparency, traceability, and human-centered outputs, allowing non-expert users to understand key financial conditions without depending on opaque analytical models. The agent is demonstrated through an illustrative scenario based on simplified financial statements representative of microenterprise contexts. This demonstration shows the internal coherence and feasibility of the design, particularly how explicit rules and narrative explanations can support financial understanding. The study does not claim empirical validation or real-world performance evaluation; rather, it offers a design-oriented foundation for future implementation and testing.*

Keywords– *Intelligent agents, financial statement interpretation, microenterprises, design science research, financial decision-making.*

I. INTRODUCTION

Microenterprises constitute the predominant component of the business fabric and play a fundamental role in job creation, local economic development, and market sustainability. However, specialized literature has consistently shown that these organizations face structural limitations in financial management, particularly in understanding and interpreting financial statements as input for business decision-making [1], [2], [3], [4]. Various studies agree that, although microenterprises tend to comply with basic accounting and financial reporting practices, this information is mainly used for formal or tax purposes, without becoming an effective strategic management tool.

This problem can be explained, to a large extent, by the gap between the generation of financial information and its understanding by the owners or managers of microenterprises. Previous research indicates that fundamental concepts such as liquidity, profitability, solvency, and indebtedness are

perceived as abstract, overly technical, or unrelated to everyday operational reality, which limits their incorporation into business planning and control processes [1], [2], [5], [6]. In this context, financial decision-making tends to be based on empirical experience or intuition, rather than on systematic analysis of financial statements, increasing the risk and economic vulnerability of these organizations.

Given these limitations, artificial intelligence (AI) has been widely explored to improve financial information analysis. Prior studies report the use of machine learning, advanced statistical models, and hybrid approaches in tasks such as financial statement analysis, business performance evaluation, accounting anomaly detection, and financial forecasting [7], [8], [9], [10]. These methods have improved efficiency and analytical accuracy, particularly in corporate and financial contexts.

However, most AI-based financial analysis systems have been developed with a strong technical orientation, prioritizing predictive performance and model accuracy over user understanding [8], [9], [11]. Consequently, many operate as “black boxes,” producing numerical outputs or recommendations without clearly explaining how the results are obtained. This limits their usefulness in microenterprises, where users often lack specialized accounting or technological expertise.

This concern has increased interest in Explainable Artificial Intelligence (XAI), especially in finance, where trust and transparency are essential. Previous studies indicate that limited explainability reduces user acceptance and generates resistance, even when system outputs are technically accurate [11], [12], [13], [14]. In this context, explainability helps users understand results, validate conclusions, reduce perceived risk, and build confidence in intelligent financial systems.

However, the literature also reflects divergent positions regarding the role of explainability in AI-based financial systems. While some authors argue that transparency is an indispensable requirement for the adoption and effective use of these systems [12], [15], Others warn that incorporating explainability mechanisms may involve trade-offs between interpretability and performance, especially in complex or large-scale models [8], [9]. This tension between technical precision and comprehensibility is one of the central debates in the design of intelligent systems applied to finance.

Additionally, studies on technology adoption in microenterprises emphasize that the acceptance of AI-based solutions depends on factors that go beyond the analytical capacity of the system. Usability, interface design, language used, and alignment with the cognitive abilities of the end user have a decisive influence on the perception of usefulness and willingness to use these technologies [4], [14], [15], [16]. Empirical research has shown that systems with complex interfaces or overly technical terminology have low adoption rates in microenterprise environments, even when their technical performance is high.

In this context, intelligent agents have emerged as an alternative for combining automated analysis, reasoning, and user communication within a single system. The literature defines them as systems capable of perceiving information, processing it through analytical models, and acting autonomously to support decision-making [12], [13], [15], [16]. In finance, they have been applied as virtual assistants and decision-support tools; however, most proposals do not explicitly address financial interpretation for microentrepreneurs or systematically incorporate explainability and usability mechanisms.

From an integrative perspective, the state of the art reveals a relevant research gap. Although prior studies have examined financial interpretation in microenterprises, AI-based financial analysis, explainability, and technology adoption, these areas are usually treated separately [4], [7], [12], [15]. Therefore, there is a lack of intelligent agent architectures specifically designed to support financial statement interpretation in microenterprises while considering users' cognitive and contextual limitations.

In methodological terms, the Design Science Research (DSR) approach has been widely recognized as an appropriate strategy for addressing complex problems by designing technological artifacts geared toward real needs. Various studies highlight that DSR allows for the integration of theory and practice, articulating processes of problem identification, artifact design, expert validation, and definition of evaluation metrics [7], [12], [17]. This approach is particularly relevant for the design of intelligent systems aimed at financial interpretation, where scientific value lies both in the proposed architecture and in the criteria used for its evaluation.

In this context, this article aims to design and conceptually demonstrate an interpretable intelligent agent for financial statement interpretation in microenterprises, using a Design Science Research approach. The proposed architecture translates technical financial information into understandable and decision-oriented insights by integrating AI techniques, explainability principles, and usability criteria. Thus, the study contributes a structured and validatable proposal that addresses gaps in prior literature and supports future empirical evaluation in microenterprise contexts.

II. THEORETICAL FRAMEWORK

A. Financial statements in microenterprises and their analytical structure

In microenterprises, financial reporting usually relies on a limited set of highly aggregated reports and items, which facilitates recording but requires translation mechanisms to convert figures into decisions [1], [2], [4], [18]. Financial interpretation is mainly based on the Statement of Financial Position, covering assets, liabilities, and equity, and the Income Statement, covering revenues, costs, expenses, and net income. These macro-items are sufficient to derive indicators of liquidity, indebtedness, activity, and profitability [18], [19].

Accounting simplification is often associated with instrumental practices, such as spreadsheets, and compliance-oriented reporting, which reinforces the need for tools that automate the sequence from financial structure to indicators and interpretation without requiring advanced accounting literacy [4], [20]. However, AI-based automation in financial statement generation or verification also introduces challenges related to quality, consistency, and compliance when records are transformed into reports [8], [21], [22], [23].

B. Financial analysis: ratios, structural reading, and accounting consistency

Financial interpretation can be formalized through ratios that synthesize relationships between accounting items and support the diagnosis of key business dimensions [18], [19], [24]. For microenterprises, a minimum set of indicators should cover liquidity, indebtedness or solvency, profitability, and efficiency or activity [18], [25]. This logic can be integrated into decision-support systems and intelligent platforms through an accounting knowledge base and a calculation-validation engine [17], [26], [27], [28].

1) Liquidity ratio (short-term payment capacity):

$$CR = CA / CL \quad (1)$$

CR: current ratio (dimensionless),
CA: current assets (monetary units),
CL: current liabilities (monetary units).

$$QR = (CA - Inv) / CL \quad (2)$$

QR: quick ratio (dimensionless),
Inv: inventories (monetary units),
CA, CL: as previously defined.

$$WC = CA - CL \quad (3)$$

WC: working capital (monetary units),
CA, CL: as previously defined.

These indicators are directly linked to the "survival reading" of a microenterprise and are useful as an explainable basis (Baseline) for its traceability [18], [24].

2) Leverage and solvency ratios:

$$\text{TDR} = \text{TL} / \text{TA} \quad (4)$$

TDR: total debt ratio (dimensionless),
TL: total liabilities (monetary units),
TA: total assets (monetary units).

$$\text{DE} = \text{TL} / \text{EQ} \quad (5)$$

DE: debt-to-equity ratio (dimensionless),
EQ: equity (monetary units),
TL: total liabilities.

$$\text{SR} = \text{TA} / \text{TL} \quad (6)$$

SR: solvency ratio (dimensionless),
TA, TL: as previously defined.

They are key to risk and stability alerts; they also align with approaches to financial risk assessment in microenterprises using AI [25], [29].

3) Profitability ratios (profit-making capacity):

$$\text{GM} = (\text{R} - \text{COGS}) / \text{R} \quad (7)$$

GM: gross margin (dimensionless),
R: revenue or net sales (monetary units),
COGS: cost of goods sold (monetary units).

$$\text{OM} = \text{OI} / \text{R} \quad (8)$$

OM: operating margin (dimensionless),
OI: operating income (monetary units),
R: revenue or net sales (monetary units).

$$\text{ROA} = \text{NI} / \text{TA} \quad (9)$$

ROA: return on assets (dimensionless),
NI: net income,
TA: total assets.

$$\text{ROE} = \text{NI} / \text{EQ} \quad (10)$$

ROE: return on equity (dimensionless),
NI: net income,
EQ: equity (monetary units).

The evolution of profitability and its explanation is central to financial analysis and forecasting systems [13], [19], [24].

4) Activity and efficiency ratios (resource utilization):

$$\text{ATO} = \text{R} / \text{TA} \quad (11)$$

ATO: asset turnover (times per period),
R: revenue,
TA: total assets.

$$\text{IT} = \text{COGS} / \text{Inv}_{\text{avg}} \quad (12)$$

IT: inventory turnover (times per period),
COGS: cost of goods sold,
Inv_{avg}: average inventory.

$$\text{DIO} = 365 / \text{IT} \quad (13)$$

DIO: days inventory outstanding (days),
IT: inventory turnover.

These ratios are particularly useful for small commercial enterprises and can be expressed using traffic lights/thresholds for educational purposes [18], [30].

C. Vertical and horizontal analysis: mathematical formalization for comparative interpretation

In addition to ratios, classic financial analysis is complemented by vertical analysis (structure) and horizontal analysis (variation over time). Both are especially valuable when simplified reports are available and it is necessary to explain “composition” and “change.” [18], [19].

1) Vertical analysis (Common-size):

Vertical analysis expresses each item as a proportion of a base total:

$$\text{VA}_{\text{SFP}}(i) = (\text{X}_i / \text{TA}) \times 100 \quad (14)$$

VA_{SFP}(i): percentage share of the item *i* part SFP (%),
X_i: item value *i* part SFP (local currency),
TA: total assets.

$$\text{VA}_{\text{IS}}(j) = (\text{Z}_j / \text{R}) \times 100 \quad (15)$$

VA_{IS}(j): percentage share of item *j* in the IS (%),
Z_j: value of item *j* in the IS (monetary units),
R: revenue.

This analysis is useful for explaining, for example, “what part of the business is committed to debt” or “how much expenses weigh on sales” in non-technical language [18], [24].

2) Horizontal analysis (temporal variation):

Horizontal analysis measures changes between two periods, the first being the absolute variation:

$$\Delta \text{X} = \text{X}_t - \text{X}_{t-1} \quad (16)$$

ΔX: absolute change (monetary units),
X_t: value of the item in the current period *t*,
X_{t-1}: value of the item in the previous period.

The percentage change is presented below:

$$\% \Delta \text{X} = (\text{X}_t - \text{X}_{t-1}) / (\text{X}_{t-1}) \times 100 \quad (17)$$

% ΔX : percentage change of the item (%),
 X_t ; X_{t-1} : as previously defined.

Operational note: if, $X_{t-1} = 0$, the percentage change is undefined; in that case, it is reported ΔX and is marked as “not calculable” for % ΔX .

This formalization supports interpretations such as “growth” or “deterioration” and is connected to approaches to prediction and economic cycles supported by ML [13], [24].

D. Risk, anomalies, and fraud: why agents should include explainable alerts

In the financial sphere, interpretation is not limited to describing ratios; it also includes identifying signs of risk, inconsistencies, or anomalous patterns. Conceptually, this is supported in the literature on fraud detection and fuzzy/ML models for financial statements, which emphasizes the need for analytical and explanatory mechanisms [14], [31], [32]. For microenterprises, these alerts should be conservative, explainable, and based on traceable criteria to avoid misinterpretation [14], [31].

E. Baseline Approach: Traceable and Pedagogical Interpretation

The Baseline is conceptualized as a system that can be explained by its construction: it is based on (i) ratio calculations, (ii) vertical/horizontal analysis, (iii) explicit accounting rules (thresholding and narrative), and (iv) consistency checks [17], [20], [26], [27]. Its theoretical purpose is to maximize traceability, auditability, and comprehension, which is consistent with contexts where the user is not a specialist [2], [4].

F. Hybrid Mode: Baseline + statistical analysis /ML + explainability (LIME/SHAP)

The Hybrid is theoretically defined as an extension of the Baseline that incorporates statistical analytics or ML to improve sensitivity to patterns, trends, and risk, while maintaining output explainability [24], [28], [29]. In terms of design, the Hybrid can incorporate supervised models commonly used in finance/accounting (trees, random forests, SVM, networks, boosting), with parsimonious selection based on available data [7], [9], [32].

In this article, the artifact is designed and demonstrated in its Baseline version (ratio calculation + structural analysis + explicit rules), prioritizing interpretability and traceability for non-expert users. The hybrid model with ML+XAI is considered a planned extension of the project and is addressed as future work, once multi-case data and empirical evaluation protocols are available.

G. Design Science Research (DSR) as the theoretical and methodological basis of the artifact

Design Science Research is conceptualized as an approach aimed at creating and evaluating artifacts to solve

practical problems, where the scientific contribution lies in evidence-based design and systematic evaluation of the artifact [12], [17], [26], [27]. In this work, the artifact is an intelligent agent integrating accounting structure, an explainable engine, and hybrid analytics, consistent with the evolution of AI-based financial analysis where value lies in the architecture and its ability to operate with real data and meaningful queries [19], [33], [34].

III. METHODOLOGY

Methodologically, the study adopts a Design Science Research (DSR) approach, recognizing artifact design as a scientific contribution when grounded in theory, addressing a relevant problem, and described rigorously. The intelligent agent is the central artifact, and the contribution lies in the design knowledge derived from its architecture, functional logic, and interpretive principles.

A. Design Science Research focused on artifact design

Design Science Research is adopted in this study from a design-oriented perspective, prioritizing the conceptual construction of the artifact rather than its technical implementation or empirical validation. Accordingly, the article is limited to the design, theoretical grounding, and conceptual demonstration of the proposed intelligent agent. No real financial statements, audited datasets, expert panels, user studies, or quantitative performance metrics are included at this stage; therefore, the contribution should be understood as a design-oriented artifact proposal, not as an empirically validated decision-support system.

This approach is consistent with engineering and information systems research, where the objective is to propose structured and theoretically grounded solutions to complex practical problems. Thus, the study does not aim to measure the agent’s performance statistically, but to define its components, their interaction, and the way in which simplified financial data can be transformed into understandable information for non-expert users.

B. Phases of Design Science Research applied in the study

Following the Design Science Research framework, the methodological process is structured into the following phases, up to the architectural design level [12], [17], [26], [27]:

1) Identification of the problem:

The central problem is the gap between the availability of basic financial statements in microenterprises and the limited ability of owners or managers to interpret them for decision-making, exacerbated by technical language, lack of context, and reliance on accountants [19], [33], [34].

2) Definition of the artifact's design objectives:

Based on the identified problem, the design objectives of the intelligent agent are established, aimed at: Facilitating the interpretation of simplified financial statements through clear and understandable explanations. Preserving the traceability

and accounting consistency of the analyses performed. Prioritizing practical usefulness and managerial understanding, without replacing the role of the accounting professional.

3) *Design of the artifact (conceptual and architectural level):*

This phase, developed in Chapter 4, constitutes the core of the study and includes the definition of the agent’s layered architecture, functional design under the Input–Process–Output paradigm, specification of key internal modules, and its conceptual abstraction in terms of perception, reasoning, and action. No software implementation or execution with real or audited data is performed.

4) *Conceptual demonstration:*

The demonstration is carried out at an illustrative level using a representative scenario and simplified financial data, with the aim of demonstrating how the device works and the traceability of the reasoning. This demonstration does not constitute statistical validation, but rather a verification of the feasibility and internal consistency of the design.

5) *Empirical evaluation as a future research stage:*

The empirical evaluation of the intelligent agent, including testing with real microenterprise financial data, expert validation, user-based usability assessment, or quantitative performance analysis, is not conducted in this stage of the study. This absence of empirical validation is explicitly recognized as a limitation of the article and is proposed as a necessary future phase of the research project. The current study focuses on artifact design, conceptual coherence, and traceable demonstration rather than on empirical effectiveness.

6) *Design communication:*

This article fulfills the communication phase of Design Science Research by documenting the problem, theoretical foundations, design methodology, and agent architecture, contributing reusable design knowledge for future AI-assisted financial interpretation research.

IV. ARTIFACT DESIGN: INTELLIGENT AGENT ARCHITECTURE

Microenterprises often struggle to interpret financial information from basic accounting reports, limiting managerial decision-making due to limited financial expertise. In response, this section presents the design of an intelligent agent that transforms simplified accounting data into interpretable, decision-oriented financial insights using a Design Science Research approach.

A. Design Objectives and Design Principles

The intelligent agent is designed according to objectives and principles addressing microenterprise needs and Design Science Research requirements, conceiving the artifact as a purposeful solution whose value lies in its utility, relevance, and rigor [34], [35].

1) Design Objectives:

The primary objective of the proposed intelligent agent is to facilitate the interpretation of financial statements in microenterprises by transforming structured accounting data into meaningful and comprehensible financial insights.

2) Design Principles:

The intelligent agent design follows principles of interpretability-by-design, minimal input requirements, modularity, and human-centered output. Analytical processes are transparent and traceable to explicit financial rules, while essential financial variables are prioritized to ensure usability in microenterprise contexts.

B. Functional Design of the Intelligent Agent

The functional design explains how structured financial data are transformed into interpretable outputs through an Input–Process–Output paradigm, as illustrated in Figure 1, emphasizing clarity and traceability.

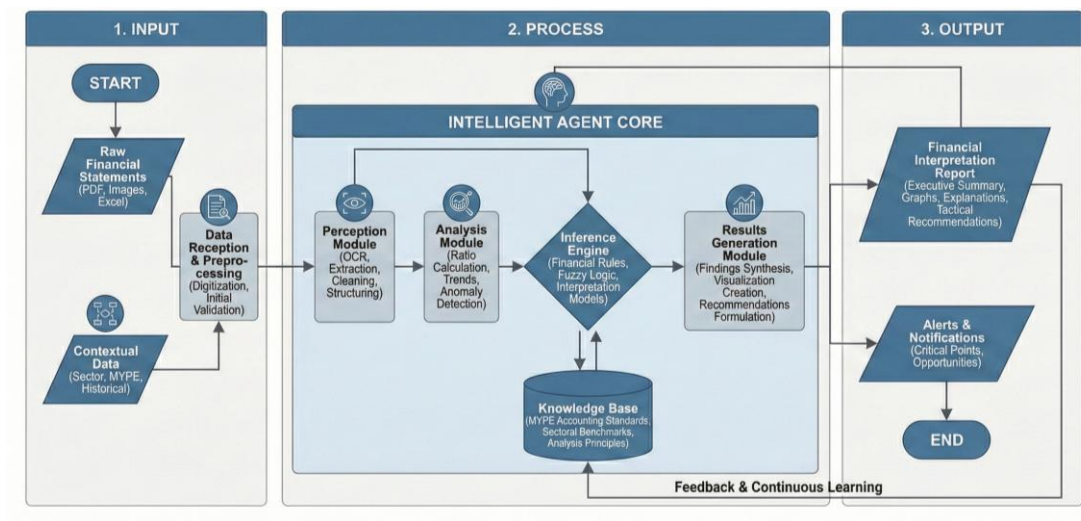


Fig. 1 Functional Design of the Intelligent Agent (Input–Process–Output).

1) Input Layer: Financial Data Acquisition:

The input layer collects and structures key financial data from simplified financial statements, focusing on essential variables and applying basic validation to ensure consistency and completeness.

2) Processing Layer: Financial Analysis and Interpretation Logic:

The processing layer forms the analytical core of the agent, combining financial ratio computation with rule-based interpretation to generate explanatory insights for microenterprise decision-making. Figure 2 provides a conceptual representation of the internal processing stages of the intelligent agent, highlighting the transformation of

structured financial data into interpretative insights through analysis, rule-based reasoning, and contextual aggregation.

Financial Ratio Computation Module:

This module computes a reduced set of financial ratios related to liquidity, profitability, and solvency using established accounting formulas. These ratios summarize financial performance and position in a form suitable for microenterprise analysis and subsequent interpretation.

Table I summarizes the financial ratios utilized by the agent, their corresponding formulas, and their interpretative purpose within the proposed design.

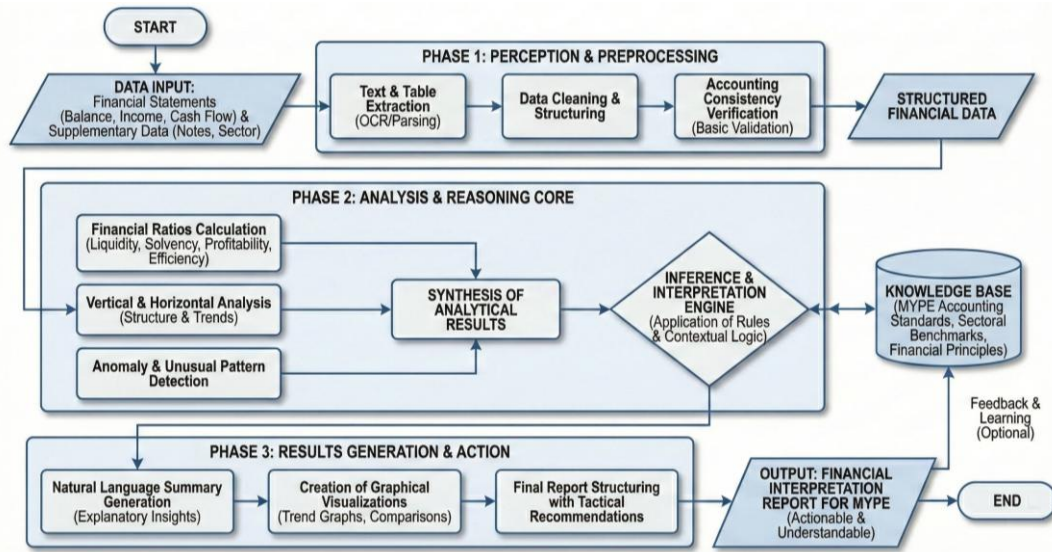


Fig. 2 Internal Processing Logic of the Intelligent Agent

TABLE I
FINANCIAL RATIOS USED BY THE INTELLIGENT AGENT

Financial Dimension	Ratio	Formula	Interpretative Purpose
Liquidity	Current Ratio	CA / CL	Evaluates short-term payment capacity
Profitability	Net Margin	NI / Revenue	Assesses operational efficiency
Solvency	Debt Ratio	Total Liabilities / Total Assets	Measures financial leverage

Note: CA = Current Assets; CL = Current Liabilities; NI = Net Income.

Rule-Based Interpretation Engine

According to Table II the rule-based interpretation engine translates computed financial ratios into qualitative assessments through explicit conditional rules grounded in conventional financial reasoning.

TABLE II
EXAMPLES OF RULE-BASED FINANCIAL INTERPRETATION

Financial Indicator	Condition	Interpretative Output
Current Ratio	< 1.0	Indicates short-term liquidity risk
Net Margin	> 10%	Reflects positive profitability performance
Debt Ratio	> 0.6	Suggests high financial leverage

The thresholds used in the rule-based interpretation engine are defined as baseline criteria based on conventional financial reasoning. For instance, a current ratio below 1.0 indicates liquidity risk because current assets are insufficient to cover current liabilities. Likewise, a debt ratio above 0.60 suggests high leverage, as liabilities represent more than sixty percent of total assets.

These thresholds are not universal or definitive. In this artifact, they serve as transparent baseline rules for conceptual demonstration. Future implementations should calibrate them according to industry, business size, accounting standards, historical behavior, and expert judgment. This preserves interpretability because each output can be traced to a specific indicator, condition, and rule.

Contextual Aggregation Module

The contextual aggregation module synthesizes individual interpretations into a coherent financial assessment. Rather than collapsing results into a single score, the agent generates a narrative overview that preserves key financial dimensions while prioritizing critical conditions relevant to microenterprise sustainability.

3) Output Layer: Interpretative Financial Reports:

The output layer generates interpretative financial reports oriented toward managerial understanding. Outputs emphasize narrative explanations over raw metrics, highlighting key financial conditions and potential risks in a clear and accessible format suitable for non-expert users.

C. Intelligent Agent Architecture

The intelligent agent architecture defines the structural organization of the artifact, supporting the transformation of financial data into interpretative outputs through modular and layered components.

1) Conceptual Architecture:

Conceptually, the intelligent agent is structured into data, analysis, interpretation, and presentation layers.

For clarity, these are abstracted in Figure 3 into perception, reasoning and processing, and action stages. This abstraction preserves functionality while providing a simplified architectural representation.

2) Logical Architecture and Technology Stack:

The logical architecture of the intelligent agent defines how the conceptual components are operationalized through software modules and data flows. It translates the layered conceptual model into an executable structure while preserving modularity, transparency, and extensibility [25], [35].

At this level, the agent is organized into modules for data acquisition, analysis, interpretation, aggregation, and presentation, each with defined inputs and outputs. This modular structure supports systematic processing, maintenance, and future enhancement, making it suitable for interpretable and adaptable decision-support systems [8], [10].

The architecture aligns with explainable AI approaches in financial decision-support systems, especially where user trust and accountability are critical [15], [30]. The technology stack prioritizes replicability and transparency, using Python because of its relevance in financial analytics, AI research, data processing, and maintainable rule-based logic [28].

The architecture is also independent of specific user interfaces or deployment environments, allowing integration into different platforms without altering the core analytical and interpretative logic. This decoupling improves the portability and sustainability of the artifact [25], [35].

Table III summarizes the main technological components that support the logical architecture of the intelligent agent and their roles within the proposed design.

TABLE III
TECHNOLOGY STACK OF THE INTELLIGENT AGENT

Component	Technology	Purpose
Data Handling	Python (DataFrames)	Financial data processing
Interpretation Logic	Rule-based engine	Explainable reasoning
Output Generation	Text-based reporting	Human-centered interpretation

D. Process Flow of Financial Interpretation

Figure 4 illustrates the end-to-end financial interpretation process implemented by the intelligent agent, from data ingestion and analysis to interpretation, aggregation, and report generation.

E. Design Justification within Design Science Research

The proposed intelligent agent is justified within the Design Science Research (DSR) paradigm, addressing a persistent gap in microenterprise contexts between financial information availability and decision-makers' ability to interpret and use it effectively [34], [35].

F. Summary of the Artifact

This section summarized the intelligent agent designed to support financial interpretation in microenterprises. The artifact integrates simplified financial data, ratio analysis, rule-based reasoning, and narrative reporting within an interpretable and modular design.

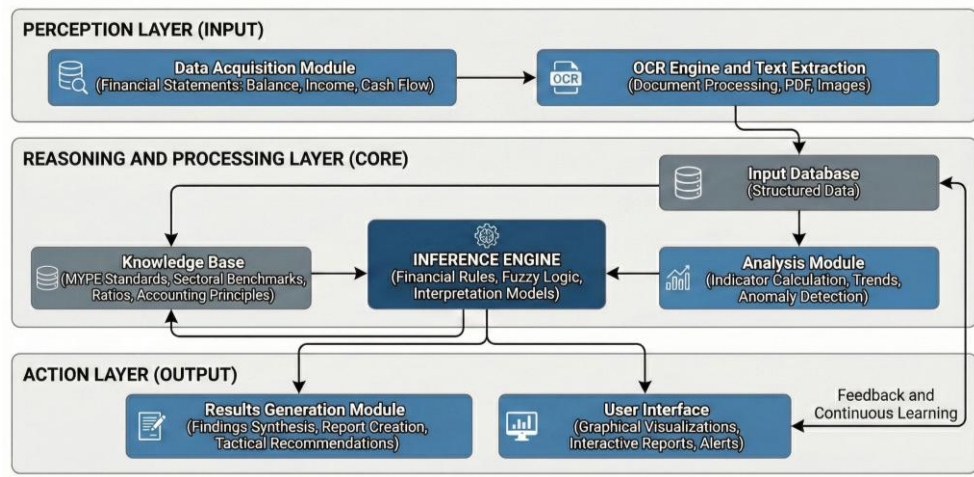


Fig. 3 Conceptual Architecture of the Intelligent Agent.

V. CONCEPTUAL DEMONSTRATION OF THE ARTIFACT

A. Conceptual Demonstration Scenario and Data Description

The proposed intelligent agent is demonstrated through an illustrative microenterprise scenario to show the artifact's internal functioning and logical coherence. This demonstration does not seek empirical validation; rather, it illustrates how simplified financial statement data can be transformed into interpretable insights through ratio calculation, rule-based reasoning, and contextual narrative aggregation [34], [35].

The financial data used are illustrative and structurally consistent with microenterprise records, but they do not represent a comprehensive or audited dataset, as shown in Table IV.

TABLE IV
SIMPLIFIED FINANCIAL STATEMENTS USED FOR DEMONSTRATION

Financial Statement	Item	Amount (USD)
Balance Sheet	Current Assets	18,000
Balance Sheet	Non-Current Assets	12,000
Balance Sheet	Total Assets	30,000
Balance Sheet	Current Liabilities	15,000
Balance Sheet	Non-Current Liabilities	5,000
Balance Sheet	Total Liabilities	20,000
Balance Sheet	Equity	10,000
Income Statement	Revenues	45,000
Income Statement	Cost of Sales	28,000
Income Statement	Gross Profit	17,000
Income Statement	Operating Expenses	12,000
Income Statement	Net Income	5,000

B. Demonstration of the Intelligent Agent Operation

Based on the simplified financial statements in Table IV, the intelligent agent computes core financial ratios that summarize the firm's liquidity, profitability, and solvency. These ratios follow standard accounting formulas and correspond to the indicators defined in the artifact design in Table I, ensuring consistency between the specification and

demonstration. Table V presents the computed ratios, which serve as inputs for the subsequent rule-based interpretation process.

TABLE V
FINANCIAL RATIOS COMPUTED FOR THE DEMONSTRATION SCENARIO

Financial Dimension	Ratio	Formula	Value
Liquidity	Current Ratio	Current Assets / Current Liabilities	1.2
Profitability	Net Margin	Net Income / Revenues	11.11%
Solvency	Debt Ratio	Total Liabilities / Total Assets	0.67

The computed financial ratios are evaluated using a rule-based interpretation engine that applies explicit conditions to transform quantitative indicators into qualitative financial assessments, ensuring transparent and traceable reasoning, as shown in Table VI.

TABLE VI
SUMMARIZES THE RULE-BASED INTERPRETATIONS GENERATED BY THE INTELLIGENT AGENT FOR THE DEMONSTRATION SCENARIO

Financial Dimension	Indicator	Condition Evaluated	Interpretative Output
Liquidity	Current Ratio (1.20)	≥ 1.0 and < 1.5	Indicates acceptable short-term liquidity, although limited margin for unforeseen obligations
Profitability	Net Margin (11.11%)	$\geq 10\%$	Reflects positive profitability performance and adequate cost management
Solvency	Debt Ratio (0.67)	> 0.60	Suggests relatively high financial leverage, requiring cautious long-term financial management

The contextual aggregation mechanism integrates individual interpretations into a coherent financial narrative that highlights critical conditions, key risks, and overall financial tendencies, supporting holistic understanding in microenterprise contexts with limited financial expertise [7], [26].

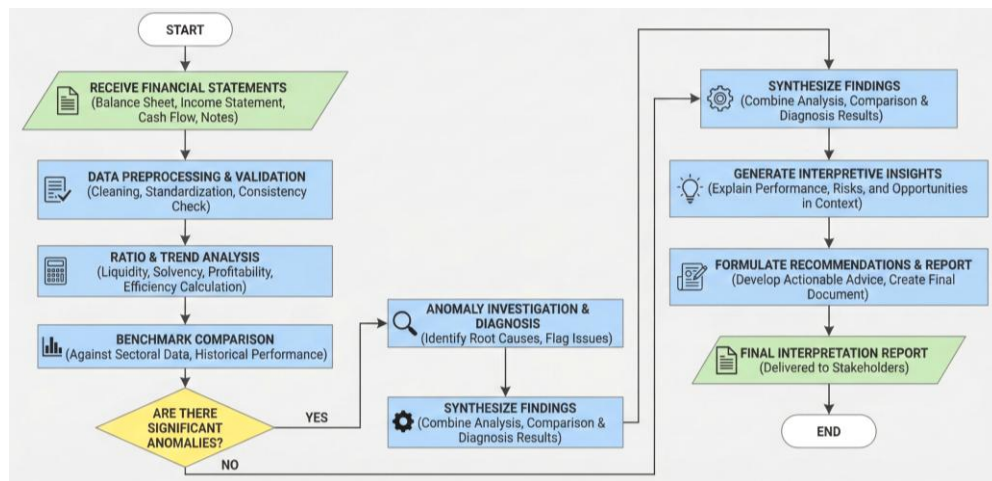


Fig. 4 Financial Interpretation Process Flow of the Intelligent Agent.

VI. DISCUSSION AND IMPLICATIONS

The design and demonstration of the intelligent agent contribute to research on financial decision-support systems for microenterprises by addressing adoption barriers related to complexity, limited interpretability, and users' financial literacy levels [7], [18], [26], [29].

The demonstration is consistent with prior studies showing that financial interpretation, rather than data availability, is a key bottleneck in microenterprise decision-making [9], [28], [31]. Unlike approaches focused on predictive analytics or advanced machine learning [23], [24], the proposed agent adopts an interpretability-driven design based on explicit reasoning and human-centered outputs. This aligns with recent calls for explainable and transparent financial decision-support systems, particularly where trust and usability are critical for adoption [15], [30], [36].

Although previous works have explored intelligent systems for financial analysis, many focus on ratio computation or anomaly detection and often assume accounting expertise [1], [12], [14]. The proposed agent extends this line of research by incorporating rule-based interpretation logic that translates numerical indicators into qualitative financial insights, addressing the interpretative gap identified in the literature [7], [8], [17].

From a methodological perspective, this study shows the suitability of Design Science Research for addressing practical financial interpretation challenges. Consistent with prior DSR studies in financial and decision-support domains [34], [35], it emphasizes artifact relevance, design rigor, and utility over large-scale empirical validation. The demonstration suggests that, even with simplified financial inputs, a well-designed intelligent agent can generate useful financial interpretations.

The findings also complement research on human-centered and explainable AI. Prior studies indicate that decision-support systems are more likely to be adopted when their reasoning is transparent and outputs are accessible [15], [28], [30]. The proposed agent reflects this principle by prioritizing narrative explanations over technical metrics, supporting managerial understanding without replacing professional judgment.

Despite these contributions, the study has important limitations. The intelligent agent was demonstrated only through a hypothetical and simplified financial scenario, without real microenterprise data, expert validation, user studies, or comparison with human financial interpretation. Therefore, it does not provide empirical evidence of effectiveness, accuracy, usability, user acceptance, or real-world performance. Additionally, the predefined rule-based thresholds may not apply equally across industries, accounting standards, countries, or business models [23], [34], [35]. Since the artifact remains at the conceptual and architectural design level, future research should evaluate it using real financial data, accounting experts, end users, and comparative interpretation tasks.

Future work should evaluate the intelligent agent across different microenterprise contexts and sectors, as suggested in studies on financial decision-support scalability [25], [26]. Further research may also incorporate adaptive or hybrid reasoning mechanisms, such as machine learning for anomaly detection, sector-specific threshold calibration, or pattern recognition, while preserving the rule-based explanation layer. This would improve analytical sensitivity without reducing transparency and traceability for non-expert users [15], [36].

Overall, this study contributes a design-driven and interpretable intelligent agent tailored to financial statement interpretation in microenterprises. Grounded in established financial analysis practices and prior literature, it provides a foundation for future empirical evaluation and practical implementation.

VII. CONCLUSIONS AND FUTURE WORK

This paper presented the conceptual design and illustrative demonstration of an interpretable intelligent agent for financial statement interpretation in microenterprises, using a Design Science Research approach. The artifact addresses the gap between available financial information and the limited interpretive capacity of non-expert decision-makers. The agent combines financial analysis techniques and rule-based reasoning to transform simplified financial data into accessible, decision-oriented insights. The demonstration shows the design's coherence and feasibility, illustrating how context-aware interpretations can be generated without opaque analytical models. The study contributes a design-oriented proposal focused on interpretability, transparency, and human-centered outputs. However, it is limited by its conceptual scope, hypothetical scenario, predefined rules, and lack of empirical validation. Future research should evaluate the agent in real accounting workflows using microenterprise data, expert assessment, usability testing, interpretability measures, and comparison with human financial interpretation.

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