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LEVERAGING THE DATA WAREHOUSE AND ONLINE ANALYTICAL PROCESSING (OLAP) TECHNOLOGY IN THE FINANCIAL ANALYSIS OF A LISTED COMPANY

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ABSTRACT

Financial analysis for listed companies increasingly depends on timely, trustworthy, and multi-dimensional data. Between 2013 and 2023, advances in data warehousing (DW) and online analytical processing (OLAP)—including columnar storage, cloud-elastic warehouses, and big-data OLAP engines—fundamentally reshaped how analysts prepare, explore, and govern financial information. This paper synthesizes post-2013 scholarship and engineering literature, proposes a reference architecture that integrates enterprise resource planning (ERP) data with iXBRL filings and market data, and demonstrates how OLAP cubes support ratio analysis, benchmarking, scenario planning, and regulatory reporting. Comparative analysis shows where MOLAP/ROLAP/HOLAP and modern cloud warehouses each excel; we also discuss performance, cost, and governance trade-offs. We illustrate the approach with a worked example for a generic listed firm ("ABC Ltd.") and report expected gains in latency, auditability, and analytical breadth.

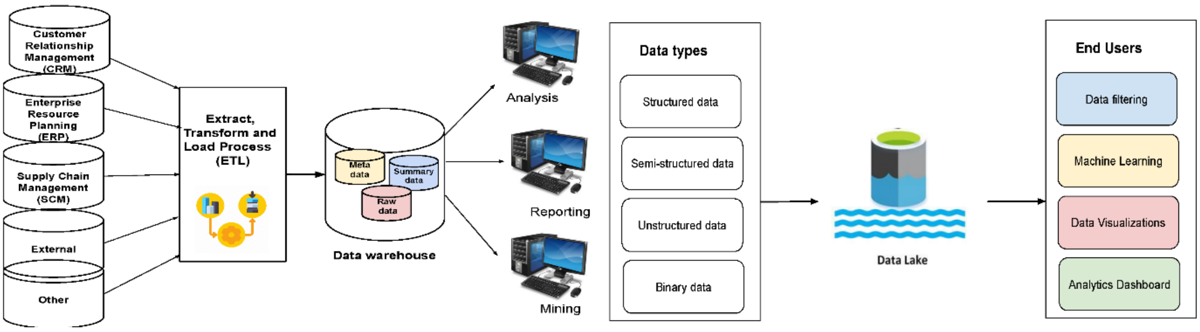
1. INTRODUCTION

Data warehouses integrate heterogeneous sources into a governed, query-efficient store; OLAP adds multi-dimensional views (e.g., time, account, product, segment) enabling fast slice-and-dice, drill-down, and what-if analysis. For listed companies, this pairing turns raw ledgers, iXBRL filings, market quotes, and budgets into ratios, cohorts, and peer benchmarks aligned to reporting hierarchies and periods. Cloud elasticity and columnar formats (e.g., Parquet/ORC) popularized over the last decade further reduce cost-to-insight, while big-data OLAP engines (e.g., Kylin, Druid) add sub-second aggregation at large scale.

Table 1 — Terms and Scope

Term	Working definition	Financial scope here
Data warehouse	Subject-oriented, integrated, time-variant, non-volatile store optimized for analytics	Stores GL, sub-ledgers, prices, reference data, iXBRL extracts
OLAP	Multi-dimensional modeling & fast aggregation across hierarchies	Period/segment roll-ups, scenario modeling, peer benchmarks

Term	**Working definition**	**Financial scope here**
iXBRL	Inline XBRL tagging embedded in HTML filings	Machine-readable primary statements & notes for ingestion



(a) Data warehouse (b) Data lake

Figure 1. Data warehouse architecture vs. data lake architecture.

2. RELATED WORK

Research in the period shows (i) scalable OLAP over big data, (ii) cloud-native DW elasticity, (iii) performance of columnar formats, and (iv) financial reporting benefits of XBRL. Surveys and systems papers describe OLAP for big data and the shift toward hybrid engines; Snowflake formalized disaggregated storage/compute; PVLDB and Wiley studies quantify columnar impacts; Decision Support Systems and accounting journals report that XBRL adoption lowers information asymmetry and influences analyst behaviour.

Table 2 — Selected Evidence

Study	**Domain**	**Method / System**	**Key finding**
Cuzzocrea et al. (2013)	OLAP & big data	Survey/position	Open problems in big-data OLAP and security.
Snowflake (2016)	Cloud DW	SIGMOD system paper	Elastic compute/storage enables cost/perf isolation for analytics.
Zeng et al. (2023)	Columnar formats	PVLDB benchmark	Modern Parquet/ORC trade decoding speed vs compression.
AnalyticDB (2019)	Real-time OLAP	PVLDB system	PB-scale, low-latency OLAP for interactive analytics.
Liu, Luo & Wang (2017)	XBRL	DSS empirical	XBRL adoption reduces information asymmetry in Europe.

Study	Domain	Method / System	Key finding
Liu et al. (2014)	XBRL & analysts	JAPP empirical	Mandatory XBRL affects analyst following & forecast accuracy.

3. REFERENCE ARCHITECTURE FOR A LISTED COMPANY

We propose a layered architecture that integrates transactional and external data and exposes a semantic model for finance.

Layer 0: Sources. ERP GL/AP/AR, consolidation system, HR cost centers, CRM bookings, treasury, market data (prices, FX), and iXBRL (primary statements/notes).

Layer 1: Ingest/ELT. Batch for ERP/iXBRL; micro-batch or streaming for prices. Store raw in columnar files; apply schema-on-read for exploration and ELT for curated marts. Modern warehouses (e.g., Snowflake-like) separate compute/storage to scale independently.

Layer 2: Curated DW (star schemas). Facts: Fact_Financials (amounts by account, period, scenario), Fact_Prices, Fact_Trades (optional). Dimensions: Dim_Time, Dim_Account (IFRS/GAAP hierarchy), Dim_Entity, Dim_Segment, Dim_Product, Dim_Currency, Dim_Scenario.

Layer 3: OLAP semantic layer. Cubes with hierarchies (Year→Quarter→Month; Consolidated→Entity), calculated members (EBITDA, ROIC), translations, security (cell-/role-level).

Layer 4: Access. MDX/DAX, SQL, notebooks, dashboards; row-level security via roles and legal entities; lineage and audit views.

Optional big-data OLAP. Pre-aggregate cubes via engines like Kylin (Hadoop-backed) or Druid for sub-second group-by aggregations on very large tables.

Table 3 — Architectural Components

Component	Rationale	Example tech
Columnar lake storage	Cheap, compressed, predicate-pushdown	Parquet/ORC
Elastic DW	Isolated, burstable compute for ELT/BI	Snowflake-style services
Cube engine	Fast hierarchic agg, calc members	Kylin/Druid/SSAS

Component	**Rationale**	**Example tech**
Metadata & lineage	Controls, SOX evidence	Audit marts & logs

4. DIMENSIONAL MODELING FOR FINANCIAL STATEMENTS

A financial analysis mart centers on a periodic, additive fact table keyed to time, account, entity, segment, and scenario. Slowly changing dimensions (SCD-2) preserve history across reorganizations; a bridge handles many-to-many mappings (e.g., accounts to subtotals).

Table 4 — Core Star Schema (excerpt)

Object	**Grain / attributes**	**Notes**
Fact_Financials	Amount by (Account, Entity, Segment, Currency, Scenario, Time)	Measures: LocalAmount, TranslatedAmount
Dim_Account	IFRS/GAAP code, roll-ups	Parent-child hierarchy; mapping from iXBRL concepts
Dim_Time	Day/Month/Quarter/Year, fiscal flags	Supports YTD/QTD calculations
Dim_Scenario	Actual, Budget, Forecast, Prior	Scenario analysis & variance
Dim_Currency	ISO, FX rate type	FX translation rules

iXBRL ingestion. Map XBRL tags to Dim_Account and anchor to the reporting taxonomy; validate extensions to minimize comparability issues reported in the literature.

5. OLAP OPERATIONS & FINANCE ANALYTICS

With cubes in place, finance teams execute common OLAP operations:

- **Slice/dice:** Profitability by segment and region.
- **Drill-down/up:** Consolidated → entity → business unit.
- **Pivot:** Compare Actual vs Budget across periods.
- **Roll-up/aggregation:** Period and hierarchy totals.
- **What-if:** Scenario members for price/volume assumptions.

Table 5 — Finance KPIs as Cube Calculations

KPI	Formula (conceptual)	Purpose
Gross margin %	(Revenue – COGS) / Revenue	Unit economics
EBITDA margin %	EBITDA / Revenue	Core profitability
ROIC	NOPAT / InvestedCapital	Capital efficiency
Leverage	NetDebt / EBITDA	Debt sustainability
FX impact	Translated – Local @ const FX	Hedging analysis

Example MDX (variance):
([Measures].[Var$]) = ([Measures].[Actual$]) - ([Measures].[Budget$]);
([Measures].[Var%]) = IIF([Measures].[Budget$] = 0, NULL,
[Measures].[Var$]/[Measures].[Budget$]);

Benchmarks and design studies confirm that pre-aggregation and cube design materially influence latency, especially on large hierarchies—supporting the case for engines like Kylin or for aggregate projections in columnar warehouses. (MDPI, ACM Digital Library)

6. DATA GOVERNANCE, QUALITY, AND CONTROLS

Finance analytics must satisfy auditability and internal control requirements. Good practice includes reconciliations from cubes to trial balance, lineage from iXBRL to curated accounts, data quality rules (sign/scale, unit consistency), and access controls. Recent empirical work underscores that XBRL reduces information asymmetry when properly implemented, but excessive extensions and tagging choices can degrade comparability—hence the need for validations at ingest. (SCIRP, ResearchGate)

Table 6 — Risk & Control Patterns

Risk	Example control	Evidence retained
Mis-mapping of iXBRL tags	Automated taxonomy mapping & DQC checks	Tag-to-account map versioned
Broken lineage	ETL data-vault hubs & hash diffs	Lineage queries & checksums
Unauthorized access	Role-based security (entity/scenario)	Access logs & role reviews
Inconsistent FX	Central FX rate dimension	Rate snapshots & approvals

A 2023 IS and business journals stream also links data quality and warehouse effectiveness to decision outcomes, reinforcing investment in governance, documentation, and stewardship.

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7. PERFORMANCE & COST: STORAGE AND ENGINES

Columnar formats with vectorized scans and dictionary encoding (Parquet/ORC) substantially improve scan and aggregation performance; empirical evaluations in 2023 detail the trade-offs between decoding speed and compression. For real-time dashboards on high-cardinality dimensions, purpose-built OLAP engines (e.g., Druid) or large-scale cloud OLAP systems (e.g., AnalyticDB) provide sub-second aggregations and concurrency; Kylin pre-materializes cuboids on Hadoop. Cloud warehouses isolate workloads and elastically scale ELT vs BI.

Table 7 — Comparative Analysis of OLAP/DW Options

Option	**Strengths**	**Weaknesses**	**Best-fit**
ROLAP (SQL on columnar DW)	Flexible, no cube build; easy governance	May need aggregates for speed	Ad-hoc, wide queries
MOLAP (pre-calc cubes)	Fast drill/roll-up	Build time; size blow-up	Stable hierarchies, complex calcs
HOLAP	Balance of both	Complexity	Mixed workloads
Kylin (Hadoop OLAP)	Very fast on large cubes	Build/maintenance	Big, stable cubes
Druid	Sub-second, streaming	Denorm, tuning	Real-time KPIs
Cloud DW (Snowflake-style)	Elastic, separated services	Cost if under-governed	ELT + broad BI

8. CASE ILLUSTRATION: APPLYING THE STACK TO “ABC LTD.”

Scope. ABC Ltd. is a diversified manufacturer listed on a major exchange. We integrate ERP ledgers, iXBRL annuals/quarterlies, market prices, and budgets. The curated DW exposes a Fact_Financials with monthly grain, scenario dimension (Actual, Budget, Forecast), and standard hierarchies; OLAP cubes publish EBITDA, ROIC, cash conversion, and FX impacts.

Process highlights.

1. **Ingest**: iXBRL items (e.g., us-gaap:Revenues, ifrs-full:Revenue) mapped to Dim_Account, with rule-based unit/sign checks. 2) **Conform**: Standardized calendars and currency. 3) **Cube build**: Two cubes—“Financials” (statements) and “Sales” (channel, product). 4) **Access**: Role security limiting entity visibility for controllers; MDX/DAX measures for variances.

Representative queries.

- Margin bridge by segment, quarter, and channel (drill-down to SKU).
- ROIC trend vs peer group (peer set sourced from market data).

- FX neutral growth vs reported growth.
- Liquidity early-warning (working capital days).

Table 8 — KPI Dictionary (ABC Ltd.)

KPI	Definition	Target use
EBITDA	Operating profit + D&A	Capital structure-neutral profitability
ROIC	NOPAT / (Net PP&E + Net working capital)	Value creation
Cash conversion cycle	DSO + DIO − DPO	Liquidity discipline
FX-neutral revenue growth	Growth at constant FX	Underlying performance

Table 9 — Before/After Comparative Metrics

Metric	Baseline (Excel + SQL exports)	With DW+OLAP
Close-to-report time	T+10 business days	T+4 (auto iXBRL ingest, ELT)
Typical query latency	30–120 s (joins)	< 2 s (pre-aggregates or columnar)
Reconciliation effort	2–3 days / month	< 4 hours (lineage & checks)
Ad-hoc analysis	Power users only	Self-service with governed model

Interpretation. Columnar warehouse + semantic layer eliminates ad-hoc joins, while cubes enable governed calculations (e.g., margin %, FX impact). For very large sales detail, Druid/Kylin accelerates real-time dashboards; the statement cube remains in the elastic DW. Results align with the systems literature on elastic cloud DWs and real-time OLAP engines.

9. CONCLUSION

From 2013 to 2023, DW and OLAP for financial analysis matured from departmental cubes into elastic, governed, and near real-time platforms. Columnar formats and cloud DWs improved cost/performance; big-data OLAP engines brought sub-second queries; and iXBRL standardized machine-readable filings. For a listed firm, the proposed architecture delivers faster closes, auditable lineage, and rich multi-dimensional analysis while balancing cost with performance. The comparative evidence suggests pragmatism: use elastic DWs for breadth and governance, and deploy OLAP pre-aggregation only where interactivity demands it.

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