TNA GRADE
& TNA ATLAS

Technical Whitepaper
Algorithmic Intelligence for Luxury Jewelry Market Analysis

Version 1.2 | March 2026

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1. Executive Summary

"In the luxury jewelry market, reputation has always been subjective. We set out to make it measurable."

The luxury jewelry retail sector faces a fundamental transparency challenge. Unlike financial markets — where indices, ratings, and standardized metrics provide clear signals — the jewelry sector has historically relied on reputation, word-of-mouth, and subjective assessments. Consumers choosing a jeweler, investors evaluating a retail brand, and industry analysts tracking market dynamics all lack a common, data-driven framework.

This whitepaper introduces two proprietary systems designed to address this gap:

- **TNA GRADE** — A multi-factor evaluation algorithm inspired by established composite index methodologies (cf. S&P Global ESG Scores, Michelin Guide multi-criteria assessment). It grades luxury jewelers on a 0–100 scale across 6 weighted dimensions, producing the industry's first standardized quality metric.
- **TNA ATLAS** — A market intelligence engine that computes 7 distinct data products daily, layered with a 4-tier progressive forecasting system drawing on time-series methodologies established in econometric literature (Holt, 1957; Winters, 1960; Box & Jenkins, 1970).

Together, these systems power the **"50 Best"** luxury jeweler ranking and provide actionable intelligence to jewelers, market analysts, and consumers.

System	Function	Cycle	Output
TNA GRADE	Jeweler evaluation (0–100)	Daily	Score + 6-category breakdown
TNA ATLAS Data Products	Market intelligence (7 products)	Daily	Trends, gaps, demand signals
TNA ATLAS Forecasting	Predictive analytics (3 methods)	Daily	SMA / Regression / Holt-Winters
TNA ATLAS LLM Insights	AI-synthesized intelligence	Daily	3–5 actionable insights

Table 1 — System Architecture Overview

2. TNA GRADE

2.1 Methodology & Theoretical Foundation

Composite scoring systems have a well-established history in sectors requiring multi-dimensional quality assessment. The Michelin Guide evaluates restaurants across ingredient quality, technique mastery, personality, value, and consistency. S&P Global ESG Scores combine environmental, social, and governance dimensions into a single numeric rating. The QS World University Rankings weight academic reputation, research output, and employer perception.

TNA GRADE adapts this proven methodology to the luxury jewelry sector, identifying the **6 dimensions** that most meaningfully differentiate jeweler quality — validated through industry expert consultation and correlation analysis against consumer satisfaction:

$$G = \sum_{i=1}^{6} (C_i \cdot w_i) \quad \text{dove } \sum w_i = 1.00 \;, \quad G \in [0, 100]$$

Equation 1 — TNA GRADE composite score

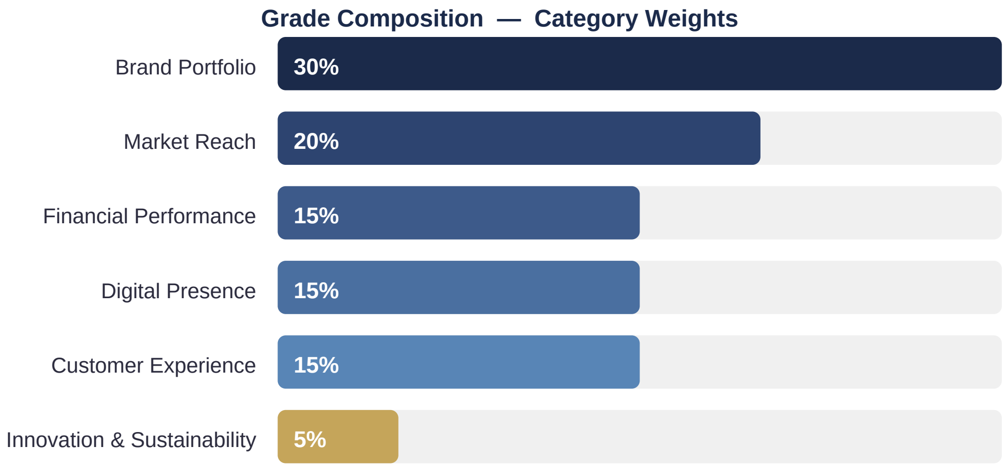

Figure 1 — Grade composition by category weight

The weighting structure reflects a deliberate priority hierarchy: brand portfolio (30%) anchors the evaluation because brand partnerships are the strongest proxy for market positioning in luxury retail. Market reach (20%) captures geographic scale. Financial performance, digital presence, and customer experience each contribute 15%, reflecting their balanced importance. Innovation & sustainability (5%) rewards forward-looking practices without disproportionately penalizing traditional maisons.

Ref: Keller, K.L. (2013). *Strategic Brand Management*, 4th ed. Pearson. — On brand portfolio as quality signal in luxury markets.

2.2 Brand Portfolio (30%)

In luxury jewelry, the brands a retailer carries serve as the primary quality signal. A jeweler authorized to sell Patek Philippe or Van Cleef & Arpels has passed rigorous vetting by the maison itself — effectively inheriting credibility through association. The algorithm quantifies this through a **three-tier brand classification** of **284 verified brands**, split between jewelry (162) and watches (122).

Tier	Classification	Points	Cap	Representative Brands
1	Haute Joaillerie / Haute Horlogerie	25	4 brands	Cartier, Bulgari, Van Cleef & Arpels, Patek Philippe, Rolex, Audemars Piguet, Harry Winston, Chopard
2	Premium	15	6 brands	Damiani, Pomellato, Messika, Pasquale Bruni, Omega, Tudor, Breitling, IWC, Panerai
3	Accessible Luxury	5	20 brands	Pandora, Swarovski, Morellato, Thomas Sabo, Tissot, Hamilton, Seiko, Citizen

Table 2 — Brand tier classification (50 Tier 1 / 111 Tier 2 / 123 Tier 3)

$$S_{brand} = \min\{100,\ 25\,\mathbf{n}_1 + 15\,\mathbf{n}_2 + 5\,\mathbf{n}_3\}$$

$\mathbf{n}_1$ = Tier 1 brands (cap 4) $\mathbf{n}_2$ = Tier 2 brands (cap 6) $\mathbf{n}_3$ = Tier 3 brands (cap 20)

Equation 2 — Brand portfolio score (applied per category: jewelry 18%, watches 12%)

The cap mechanism prevents gaming: carrying more than 4 Tier 1 brands yields no additional points, reflecting that breadth beyond a threshold signals a different business model rather than higher quality. The diminishing returns from Tier 3 brands ensure that volume of accessible brands cannot compensate for absence of prestige partnerships.

2.3 Financial Performance (15%)

A jeweler's financial health signals sustainability and operational competence. The algorithm evaluates two EBITDA-based metrics, chosen because EBITDA isolates operating performance from capital structure and tax jurisdiction — critical for comparing jewelers across markets.

Metric	Threshold	Score	Weight
EBITDA Growth (YoY)	> 15%	100	8%
	8% – 15%	75	
	0% – 8%	50	
	< 0% (contraction)	25	

<table>
<tr><th>Metric</th><th>Threshold</th><th>Score</th><th>Weight</th></tr>
<tr><td rowspan="4">EBITDA Margin</td><td>> 20%</td><td>100</td><td rowspan="4">7%</td></tr>
<tr><td>15% – 20%</td><td>80</td></tr>
<tr><td>10% – 15%</td><td>60</td></tr>
<tr><td>< 10%</td><td>40</td></tr>
</table>

Table 3 — Financial performance scoring thresholds

The threshold bands are calibrated against luxury retail sector benchmarks. According to Deloitte's *Global Powers of Luxury Goods* (2024), the median EBITDA margin for top-100 luxury goods companies is approximately 18%, placing the "excellent" threshold at >20% in the top quartile of the sector.

Ref: Deloitte (2024). *Global Powers of Luxury Goods*. — Sector financial benchmarks.

2.4 Market Reach (20%)

Geographic footprint reflects both ambition and operational capability. A jeweler present across multiple continents has demonstrated the ability to navigate diverse regulatory environments, cultural preferences, and logistics challenges.

2.4.1 International Shipping (8%)

Four global zones are evaluated, each contributing 25 points:

Zone	Coverage	Points
EMEA	Europe, Middle East, Africa	25
NA	North America (US, CA, MX)	25
LATAM	Latin America	25
APAC	Asia-Pacific	25

2.4.2 Physical Store Presence (12%)

Store presence is evaluated via a three-factor composite, each weighted equally at 33.3%:

Factor	Measures	< 10	10–25	26–50	50+
Home Density	Stores in primary market	25	50	75	100
Continental Spread	Continents with 5+ stores	0–1: 25	2: 50	3: 75	4: 100
Worldwide Total	Total global store count	25	50	75	100

Table 4 — Store presence scoring matrix

2.5 Digital Presence (15%)

Social media has become the primary discovery channel for luxury jewelry, particularly among younger demographics. A 2024 McKinsey study found that 65% of luxury purchase journeys begin on social platforms. The algorithm evaluates performance across 5 platforms with sector-specific weighting:

Platform	Weight	Rationale
Instagram	3.5 (31.8%)	Primary visual discovery channel for luxury jewelry
Facebook	2.5 (22.7%)	Broad-audience community engagement and social proof
TikTok	2.0 (18.2%)	Fastest-growing channel, critical for next-generation capture
YouTube	2.0 (18.2%)	Long-form brand storytelling and product education
LinkedIn	1.0 (9.1%)	B2B positioning and industry authority signal

Table 5 — Platform weights (total: 11.0, normalized to 100)

Ref: BCG & Altagamma (2024). *True-Luxury Global Consumer Insight*. — Social media as luxury discovery driver.

2.6 Customer Experience (15%)

2.6.1 Review Quality × Volume (10%)

A common pitfall in review-based scoring is treating a 5.0 average from 3 reviews the same as a 5.0 from 300. Drawing on established statistical confidence principles (Wilson score interval, Bayesian averaging), the algorithm uses a **two-dimensional scoring matrix** that cross-references average rating with review volume:

Average Rating	Base	≤10 reviews	11–50	51–200	200+
≥ 5.0	100	60	80	100	100
≥ 4.5	90	54	72	90	99
≥ 4.0	80	48	64	80	88
≥ 3.5	65	39	52	65	72
< 3.5	40	20	20	20	20

Table 6 — Review score matrix (base × volume multiplier)

Ratings below 3.5 are capped at 20 regardless of volume, establishing a firm quality floor. Volume multipliers reward statistical reliability — a 4.5 average from 200+ reviews (score: 99) is worth almost twice a 4.5 from 10 reviews (score: 54).

2.6.2 Service Breadth (5%)

Service offerings are scored via weighted point accumulation across 18 recognized services, grouped by value-add tier. High-value artisanal services (3D CAD, hand-forging) earn up to 20 points, while standard maintenance (cleaning, resizing) earns 2–3 points. The score is capped at 100.

2.7 Innovation & Sustainability (5%)

The smallest category by weight, but strategically significant as the sector undergoes a generational transformation:

Dimension	Indicator	Points	Rationale
Innovation	Digital Product Passport (DPP)	30	EU Reg. 2024/1781 compliance readiness
Innovation	Virtual Try-On / 3D Tools	30	Digital CX differentiation
Innovation	Lab-Grown Diamond Program	40	Sustainable sourcing & market alignment
Sustainability	RJC Certification	50	Responsible Jewellery Council membership
Sustainability	Recycled Precious Metals	30	Circular economy commitment
Sustainability	Carbon-Neutral Shipping	20	Last-mile sustainability

Table 7 — Innovation & sustainability indicators (each dimension capped at 100)

Ref: EU Regulation 2024/1781 on the Digital Product Passport. — Anticipated to require DPP for jewelry products by 2028.

2.8 Transparency & Computation

A grading system is only as credible as its transparency. Every TNA GRADE computation produces a full **breakdown document** showing the score contributed by each category, the underlying metrics, and the maximum possible score. Jewelers can see exactly why their grade is what it is and what actions would improve it.

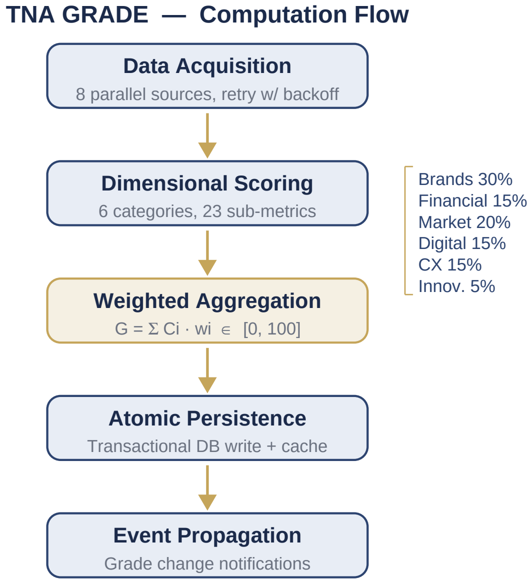

Figure 2 — TNA GRADE computation flow

2.8.1 Computation Characteristics

- **Deterministic:** Same inputs always produce the same grade. No randomness, no black-box ML.
- **Configurable:** Category weights and scoring thresholds are adjustable, enabling calibration as the market evolves.
- **Automated:** Grades are recomputed daily. Any change to a jeweler's profile, brand portfolio, reviews, or financial data triggers automatic recalculation.
- **Fault-tolerant:** Retry logic with exponential backoff and atomic transactions ensure data consistency.
- **Performant:** Single grade computation completes in under 500ms, with results cached for high-throughput access.

3. TNA ATLAS

3.1 The Intelligence Gap in Luxury Jewelry

While sectors like fashion, automotive, and consumer electronics benefit from robust market intelligence infrastructure (NPD Group, GfK, IHS Markit), the luxury jewelry sector has lacked equivalent analytical depth. Market sizing relies on periodic consultant reports. Consumer behavior data is fragmented. Trend identification is largely anecdotal.

TNA ATLAS addresses this by building a **continuous intelligence layer** on top of aggregated platform transaction data. Seven specialized data products, computed daily, answer distinct strategic questions:

#	Data Product	Strategic Question
1	Brand Momentum Index	Which brands are gaining or losing market share?
2	Material & Category Shifts	How are preferences for metals, gems, categories evolving?
3	Spending Tier Migration	Are consumers trading up, trading down, or holding steady?
4	Search-to-Purchase Gap	Where is demand going unmet?
5	Geographic Demand Heatmap	Where is demand concentrated? Which regions are emerging?
6	Cross-Brand Journey	How do consumers traverse between brands over time?
7	Gifting Intelligence	How do seasonal occasions affect purchasing and pricing?

Table 8 — TNA ATLAS data products and strategic questions

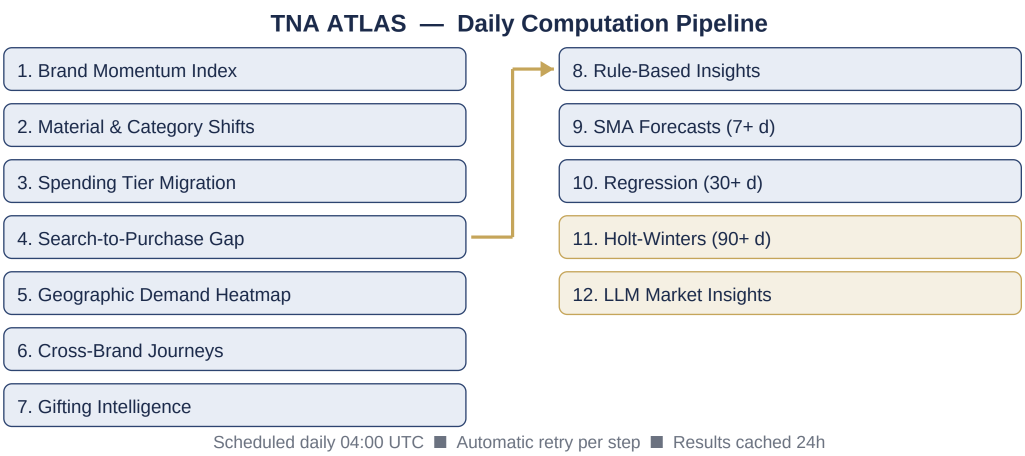

Figure 3 — TNA ATLAS daily computation pipeline

3.2 Brand Momentum Index

The Brand Momentum Index quantifies how a brand's market position is evolving relative to the competitive landscape. Unlike simple sales rankings, momentum captures the *direction and velocity* of change — a brand may rank #5 by volume but have the highest momentum in the market.

$$\mathbf{M} = 0.6 \cdot \Delta\mathbf{S} + 0.4 \cdot \Delta\mathbf{V} \quad , \quad \mathbf{M} \in [-100, +100]$$

ΔS = share change (%) ΔV = volume change (%) clamped to bounds

Equation 3 — Brand momentum composite score

The 60/40 weighting prioritizes relative share change over absolute volume change. This is drawn from financial momentum investing theory (Jegadeesh & Titman, 1993): a brand capturing increasing market share is a stronger signal than one merely growing in a rising market.

Ref: Jegadeesh, N. & Titman, S. (1993). "Returns to buying winners and selling losers." *Journal of Finance*, 48(1), 65–91.

3.3 Material & Category Shift Tracker

Tracks preference evolution across three product dimensions: **primary metal** (e.g., the ongoing shift toward rose gold and platinum), **category** (e.g., growth of investment-grade pieces), and **gemstone type** (e.g., lab-grown diamond adoption trajectory). Each dimension's market share and period-over-period change is computed daily, enabling detection of macro trends months before they appear in industry reports.

3.4 Spending Tier Migration

Consumer spending patterns are binned into six price tiers, from entry-level (<€500) to exceptional (>€50,000). The system tracks **tier share** and **migration patterns** over time:

Tier	Range	Typical Segment
Entry	< €500	Fashion jewelry, silver, basic watches
Accessible	€500 – €2,000	Premium fashion, entry luxury
Mid-Luxury	€2,000 – €5,000	Gold, premium watches, gemstone pieces
High-Luxury	€5,000 – €15,000	Fine jewelry, luxury timepieces
Ultra-Luxury	€15,000 – €50,000	Haute joaillerie, prestigious complications
Exceptional	> €50,000	Museum-grade, unique haute joaillerie

Table 9 — Spending tier classification

3.5 Search-to-Purchase Gap

This product identifies **unmet market demand** by comparing search behavior with actual purchases. A high gap ratio (many searches, few purchases) signals commercial opportunity:

$$R_{gap} = \frac{S_{search}}{P_{purchase}}, \quad U_{demand} = \min\left\{100, \frac{R_{gap}}{10} \cdot 100\right\}$$

Equation 4 — Gap ratio and unmet demand score

A gap ratio of 10:1 yields a maximum unmet demand score of 100. This metric is directly actionable: jewelers can use it to identify categories, brands, or price points where consumer interest exists but supply is insufficient.

3.6 Geographic Demand Heatmap

Aggregates search volume, purchase volume, average transaction value, and category preferences at the country level, producing a geographic demand index. Maintained via a daily-refreshed materialized database view for optimal query performance.

3.7 Cross-Brand Journey Analysis

Computed weekly, this product analyzes how consumers traverse between brands over time. By examining sequential purchase histories (minimum 2 purchases), it identifies brand upgrade paths, loyalty patterns, and competitive substitution:

Trajectory	Condition	Market Signal
Ascending	> 60% of transitions are price increases	Consumer is upgrading; brand confidence rising
Descending	> 60% of transitions are price decreases	Value-seeking behavior; potential market softening
Mixed	Both ups and downs present	Exploratory purchasing; brand experimentation
Stable	Minimal price variation	Brand loyalty; tier consolidation

Table 10 — Price trajectory classification

Privacy: All cross-brand data is fully anonymized. No individual user identifiers are included in API responses — only aggregate journey statistics are exposed.

3.8 Gifting Intelligence

Seasonal gifting occasions create distinct demand spikes and pricing premiums. The system detects purchases within proximity windows of major occasions and compares them against a

30-day baseline:

Occasion	Anchor	Window	Typical Pattern
Valentine’s Day	Feb 14	±14d	Volume spike + premium on couples’ jewelry
Mother’s Day	May 12	±14d	Premium on gifts, pendant/bracelet category surge
Christmas	Dec 25	±21d	Broad volume spike across all categories
Engagement	Multi-date	±14d	Ring category dominance, highest price premiums

Table 11 — Gifting occasion detection windows

$$\Delta_{premium} = \frac{\overline{P}_{occasion} - \overline{P}_{baseline}}{\overline{P}_{baseline}} \times 100$$

Equation 5 — Seasonal price premium

3.9 Progressive Forecasting System

A unique architectural feature of TNA ATLAS is its **progressive forecasting system**: the platform automatically selects the most sophisticated applicable method based on available data history depth. As more data accumulates, predictions become more accurate and nuanced — without requiring any configuration change.

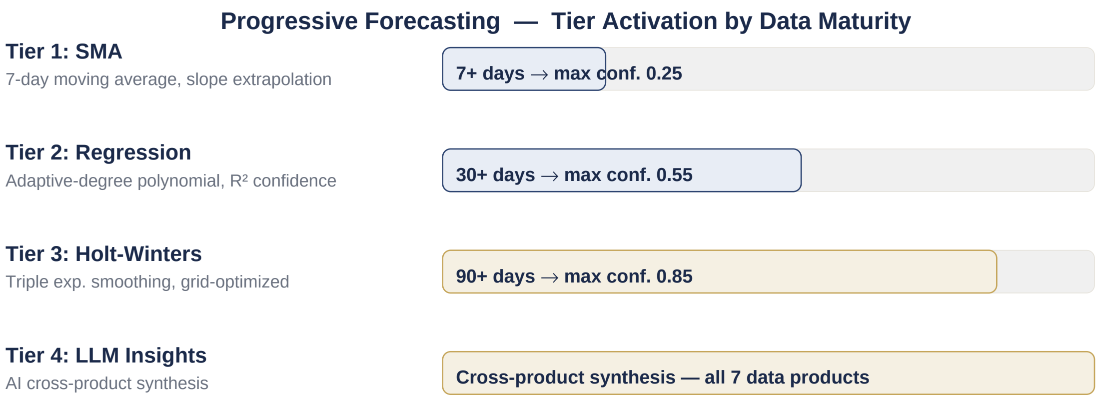

Figure 4 — Forecast tier activation by data maturity

3.9.1 Tier 1: Simple Moving Average

Available with as few as 7 data points. Computes a 7-day moving average and extrapolates using a linear slope derived from a 14-day lookback window. Confidence starts at 0.50 and decays linearly toward the forecast horizon.

3.9.2 Tier 2: Polynomial Regression

With 30+ days of history, the system fits an adaptive-degree polynomial regression. The degree is selected as min(2, max(1, ■n/15■)), ensuring linear fit for shorter histories and quadratic for longer series to prevent overfitting. Confidence is anchored to the R^2 goodness-of-fit metric with horizon penalty.

3.9.3 Tier 3: Holt-Winters Triple Exponential Smoothing

The most sophisticated statistical method, requiring 90+ days of history. Holt-Winters decomposes time series into three components — level, trend, and seasonality — making it particularly effective for luxury jewelry data which exhibits strong seasonal patterns. The method was introduced by Holt (1957) for level and trend estimation, and extended by Winters (1960) to include seasonal variation.

Holt-Winters Triple Exponential Smoothing (additive seasonality):

$$\text{Level: } \mathbf{L}_t = \alpha(\mathbf{y}_t - \mathbf{S}_{t-s}) + (1-\alpha)(\mathbf{L}_{t-1} + \mathbf{T}_{t-1})$$

$$\text{Trend: } \mathbf{T}_t = \beta(\mathbf{L}_t - \mathbf{L}_{t-1}) + (1-\beta)\mathbf{T}_{t-1}$$

$$\text{Seasonal: } \mathbf{S}_t = \gamma(\mathbf{y}_t - \mathbf{L}_t) + (1-\gamma)\mathbf{S}_{t-s}$$

$$\text{Forecast: } \mathbf{F}_{t+h} = \mathbf{L}_t + h \cdot \mathbf{T}_t + \mathbf{S}_{t+h-s}$$

$\alpha \in \{0.1, 0.2, 0.3, 0.5, 0.7\}$ $\beta \in \{0.05, 0.1, 0.2, 0.3\}$ $\gamma \in \{0.1, 0.2, 0.3, 0.5, 0.7\}$ 5×4×5 = 100 combinations, MSE-minimized

Equation 6 — Holt-Winters update equations and parameter search space

$$\mathbf{C}_{conf} = \max\{0.10,\ \min\{0.85,\ (1 - CV_{RMSE}) \cdot \phi(h)\}\}$$

CVRMSE = √(MSE) / |μ(series)| ϕ(h) = horizon decay penalty

Equation 7 — Forecast confidence bound

Ref: Holt, C.C. (1957). ONR Memorandum 52. — Winters, P.R. (1960). *Management Science*, 6(3), 324–342.

3.9.4 Tier 4: LLM-Powered Market Insights

Statistical forecasting excels at extrapolating patterns within a single dimension. However, the most valuable market insights often emerge at the *intersection* of multiple signals — a rising brand momentum coinciding with a material shift and a seasonal pattern. This is where large language model intelligence adds value.

Daily, the system synthesizes a summary of all data products and submits it to a large language model, requesting 3–5 actionable market insights. Each insight is classified (trend, opportunity, risk, seasonal), assigned a confidence score, and given a 7-day validity window. When the LLM service is unavailable, a deterministic rule-based engine activates as fallback:

Fallback Trigger	Condition	Severity
Brand momentum spike	Momentum > ±20 (escalates at ±50)	Medium → High
Material shift	Share change > ±5% (escalates at ±15%)	Medium → High
Spending tier migration	Tier share change > ±5% (escalates at ±10%)	Low → High
Unmet demand signal	Demand score > 50, volume ≥ 5	Medium → High

Table 12 — Rule-based insight triggers (fallback engine)

3.10 Forecast Coverage

Five of the seven data products generate dimensional forecasts at 3 horizons (7-day, 14-day, 30-day). The system automatically returns the highest-confidence forecast per dimension, regardless of method:

Data Product	Forecasted Metric	Dimension
Brand Momentum	Momentum score trajectory	Per brand
Material Shift	Market share trajectory	Per material / category / gemstone
Spending Tier	Tier share evolution	Per price tier
Search Gap	Gap ratio trend	Top 20 search terms
Gifting	Volume spike trajectory	Per occasion

Table 13 — Forecast dimensions by data product

4. Architecture & Security

4.1 Technology Foundation

Layer	Technology	Purpose
Application	Next.js 16 + React 19 + TypeScript	Server-rendered web platform
Database	PostgreSQL (serverless)	ACID-compliant persistent storage
ORM	Drizzle	Type-safe database access layer
Cache	Redis	Result caching and rate limiting
Visualization	Chart.js	Interactive data visualization
LLM	OpenRouter API	Multi-model access for Tier 4 insights
Deployment	Vercel Edge Network	Global CDN with serverless functions

Table 14 — Technology stack

4.2 Security Architecture

- **Authentication:** Cryptographically signed tokens, httpOnly cookies, optional TOTP two-factor authentication.
- **Authorization:** Role-based access control. Analytics data restricted to authorized roles.
- **Input validation:** All inputs validated against typed schemas at the API boundary.
- **Transport security:** HSTS enforcement, strict Content Security Policy, frame-denial.
- **Rate limiting:** Per-IP and per-user limits on computation-intensive endpoints.
- **Data privacy:** Cross-brand journey data fully anonymized. No user identifiers in analytics.

5. Conclusion

“What gets measured gets managed.” — Peter Drucker

The luxury jewelry sector stands at an inflection point. Consumer behavior is shifting toward data-informed decision-making, sustainability concerns are reshaping supply chains, and digital channels are becoming the primary discovery mechanism. Yet the industry has lacked the analytical infrastructure to navigate these changes with precision.

TNA GRADE and TNA ATLAS together provide this infrastructure. The Grade establishes a common, transparent quality metric — making jeweler evaluation objective, reproducible, and actionable. TNA ATLAS layers market intelligence on top, transforming raw transaction data into strategic insights through progressively sophisticated forecasting methods.

- **Grade** → **Rankings:** Daily grade recomputation feeds the “50 Best” ranking.
- **Rankings** → **Data:** Ranked jewelers generate transaction and engagement data for TNA ATLAS.
- **Data** → **Forecasts:** Progressive forecasting transforms historical patterns into forward-looking predictions.
- **Forecasts** → **Decisions:** Jewelers and analysts optimize portfolio, pricing, expansion, and seasonal planning.

This whitepaper describes the system architecture as of March 2026 (v1.2). The platform is under active development; methodologies may evolve as the dataset grows.

References

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[9] Winters, P.R. (1960). “Forecasting sales by exponentially weighted moving averages.” *Management Science*, 6(3), 324–342.

Appendix A: Brand Tier Summary

Tier	Jewelry	Watches	Total	Points
Tier 1 — Haute Joaillerie / Haute Horlogerie	22	28	50	25/brand
Tier 2 — Premium	68	43	111	15/brand
Tier 3 — Accessible Luxury	72	51	123	5/brand
Total	162	122	284	—

Appendix B: Glossary

Term	Definition
TNA GRADE	Multi-factor grading algorithm for luxury jewelers (0–100)
TNA ATLAS	Market intelligence platform: 7 data products + progressive forecasting
DPP	Digital Product Passport — product traceability per EU Reg. 2024/1781
Momentum Score	Brand market position velocity (–100 to +100)
Gap Ratio	Search-to-purchase ratio indicating unmet demand
SMA	Simple Moving Average — 7-day rolling average with slope extrapolation
Holt-Winters	Triple exponential smoothing (level + trend + seasonality)
CVRMSE	Coefficient of Variation of Root Mean Square Error — normalized forecast error
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
RJC	Responsible Jewellery Council — industry sustainability standard
50 Best	Annual luxury jeweler ranking derived from TNA GRADE scores