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Crowdsourced the assessment of wine rating: professional wine competition rating *vs* vivino rating

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Abstract. We evaluate wine ratings by comparing data from two crowdsourcing platforms - Vivino, which aggregates the opinions of a large number of wine lovers, and Global Wine Medal Rating, which aggregates the scores from more than 1030 international wine competitions since 2020. The study analyzes the ratings of over 120,000 wines that have participated in professional wine competitions since 2020 and which, collectively, have received over 439,000 medals during that time. The aggregated results of the wines' participation in wine competitions were compared with the scores of these wines in the Vivino rankings. Possible reasons for significant discrepancies in the scores of wines in wine competitions and Vivino were analyzed when such discrepancies occur. Overall, our results demonstrate that crowdsourced ratings are a reliable source of information for both consumers and producers. But the ability to easily compare ratings from different crowdfunding platforms, which form ratings according to different criteria, makes it much easier for the end consumer to choose a wine depending on their preferences for the type of rating or to find wines that have comparably high scores in different crowdsourced ratings.

1. Introduction

Wine is widely recognized as an experience good, where quality is difficult to evaluate prior to consumption. Over the past decades, wine ratings have emerged as critical tools for mitigating this information asymmetry, offering signals of quality that influence both consumer choice and market pricing. Traditionally, these signals have come from professional critics, whose expertise is often authoritative but inherently subjective and varied.

Recent years have seen the rise of consumer-powered platforms like Vivino, which crowdsource opinions from a large base of everyday wine drinkers. Studies such as those by Cardebat et al. (2023) have shown that Vivino scores increasingly outweigh expert ratings in terms of influence on pricing and consumer trust. Yet a third major channel for evaluation—professional wine competitions—remains largely unexamined in academic literature, despite being ubiquitous in the wine industry.

This paper introduces and analyzes the Global Wine Medal Rating (GWMR), the first comprehensive system for aggregating and normalizing results from international wine competitions. We compare GWMR scores with Vivino ratings for the same wines. This dual analysis provides a novel opportunity to evaluate two distinct forms of crowdsourced assessments: one from consumer preference, and one from professional peer judgment.

We explore the correlation, discrepancies, and implications of these two systems, with a view toward improving transparency, comparability, and reliability in wine rating practices. In doing so, we seek to better understand the relative roles these ratings play in guiding market behavior.

2. Related literature

The literature on wine rating systems can be broadly categorized into studies on expert score standardization, consumer review impact, hedonic pricing, and market signaling.

Cardebat and Paroissien (2015) were among the first to develop a non-parametric framework to standardize expert scores, accounting for divergent scales and rating tendencies. This followed earlier concerns about subjectivity and inconsistency in expert evaluations raised by Ashton (2012, 2014) and others. Their findings underscore the need for caution when comparing or aggregating scores across critics.

Parallel to the expert discourse, platforms such as Vivino have gained momentum by democratizing wine reviews. Cardebat et al. (2023) and Oczkowski and Pawsey (2019) provided robust econometric evidence that consumer ratings can now rival, and even surpass, professional evaluations in terms of their effect on wine pricing and purchase behavior. These peer-based systems are increasingly viewed as credible signals in the wine market.

Several studies have applied hedonic pricing models to examine how extrinsic and intrinsic wine attributes—including scores—impact prices. Lecocq and Visser (2006), Landon and Smith (1997), and Schamel (2003) show that quality signals, whether via experts or peer consensus, play a critical role in value perception.

Despite their commercial prominence, wine competition medals have rarely been studied in depth. Existing literature (e.g., Cavicchi et al., 2013; Benfratello et al., 2009) typically treats them as marketing artifacts rather than structured, quantifiable rating systems. No prior research, to our knowledge, has attempted to harmonize competition results into a continuous score or compare them systematically with critics or consumer ratings.

By integrating medal-based evaluations (GWMR) into the academic discourse, this study seeks to fill that gap. We aim to build a bridge between two forms of crowdsourced quality assessment—peer-to-peer (Vivino) and peer-reviewed professional judging— within a shared analytical framework.

3. Data and dataset description

This study relies on two major sources of crowdsourced wine evaluation: professional wine competition outcomes and consumer-generated ratings via the Vivino platform. These sources were independently aggregated, standardized, and then matched to facilitate comparative analysis.

3.1. Global wine medal rating (GWMR)

The Global Wine Medal Rating (GWMR) is a unique aggregation system that consolidates results from international wine competitions into a unified, normalized score. The dataset includes over 439,000 individual medal awards collected from 1035 competition events between 2020 and 2025. These awards span more than 294,000 wines produced by over 31,000 wineries in 78 countries.

The GWMR algorithm accounts for:

– Medal type (e.g., Gold, Silver, Bronze).
– Prestige and historical reliability of the competition.

These factors are synthesized to produce a GWMR score on a normalized 0–100 scale for each wine and vintage.

3.2. Vivino ratings

Vivino is a globally used consumer wine review platform where users rate wines on a 5-point scale. The dataset extracted from Vivino includes:

– Average rating per wine and vintage
– Total number of reviews
– Vintage-specific scores (when available)
– Review distribution and reliability proxies (e.g., number of raters per score)

Only wines that had both Vivino scores and GWMR medals were retained for this study, resulting in a high-confidence, dual-sourced dataset.

3.3. Matching procedure and sata cleaning

Matching was performed using a combination of fuzzy string logic, metadata alignment (vintage, producer), and manual validation. Normalization of wine names included removal of suffixes (e.g., 'Reserve', 'Gran Selezione'), standardizing casing, and filtering out non- wine entries. A combination of automated and supervised methods was used to ensure matching accuracy.

The final dataset consists of approximately 85,000 wines, each with both a GWMR score and a Vivino rating, representing a large and diverse cross-section of the global wine market.

4. Methodology of score construction

4.1. Global wine medal rating (GWMR)

The Global Wine Medal Rating (GWMR) is a quantitative framework designed to standardize and aggregate awards received by a wine in international competitions. Unlike traditional expert scores or consumer reviews, the GWMR reflects the collective judgment of professional juries across multiple events. The objective is to convert heterogeneous, often categorical medal data into a continuous score on a 0– 100 scale, accounting for both the type and context of awards.

4.1.1. Medal type valuation

In competitions that report only medal categories (e.g., 'Gold,' 'Silver,' 'Bronze') but do not publish specific numeric scores, the GWMR methodology employs an award distribution model to infer a statistically grounded score for each medal type (Figure 1). This is based on an analysis of real distributions from competitions that do provide raw scores alongside medals.

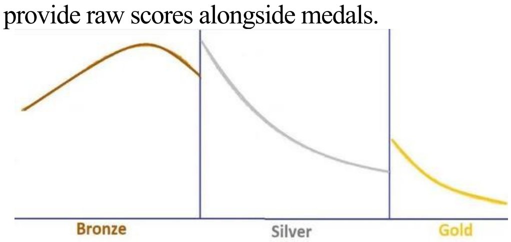

Figure 1. Distributions for different award values.

4.1.2. Award points distribution model

Medals with exponential distributions (e.g., silver, gold) have a pronounced component of:

$\lambda e^{-\lambda x}$

Empirically, we have obtained the average score is not computed as a simple midpoint but derived from the expected value of the exponential distribution (1).

$$\lambda = \frac{\pi}{N} \Rightarrow \quad \mathrm{Mean}_{\mathrm{medal}} = X_{\min} + \frac{N}{\pi} \qquad (1)$$

Where:

- $N = X_{\max} - X_{\min}$ is the number of score
- units within the medal's defined range,
- $X_{\min}$ and $X_{\max}$ are the lower and upper bounds of the medal's score interval.

This mean is systematically greater than the arithmetic average, reflecting the skewed nature of judge-based scoring in professional tasting competitions. For example, for the "silver" intervals 88–92 and 85–95, the average values will be 89.27 and 88.18, respectively.

4.1.3. Bronze medal adjustment

With an increase in the number of segments, i.e. range of scores, the "tail" of the graph is significantly lengthened, the "cliff" on the right is actually kept at the N-1 level (Figure 1).

In general, this distribution looks like this (2).

$$tx = \frac{\left(\frac{x-1}{N}\right)^{N-2} - \left(\frac{x-1}{N}\right)^{N-1}}{2\log_{N+2-x}(x) + 1} \qquad (2)$$

The average value of this distribution should be added to the minimum value of the "bronze" range.

Thus, at the first stage, for competitions where only the type of award and the range of points are indicated, we calculate the average value and assign this value to this wine in this competition.

$$g_x^0 = G_{\min} + \frac{G_{\max} - G_{\min}}{\pi}$$

$$s_x^0 = S_{\min} + \frac{S_{\max} - S_{\min}}{\pi}$$

$$b_x^0 = B_{\min} + \frac{\sum_{i=2}^{N} t_i}{\sum_{j=2}^{N} t_j}$$

Where $X_{\max}$ is the upper limit of the score range of the corresponding award, $X_{\min}$ is the lower limit of the score range, t_i is the corresponding element of the distribution.

4.1.4. Final calculations

For each wine-medal pair:

- If a specific score is published by the competition
- - use it directly.
- If only the medal category is provided - compute the interval-based expected value using the appropriate formula.
- Adjusted values are then used as input in the final aggregation and competition-weighted scoring steps.

Importantly, since the numeric range for each medal category can vary between competitions, the average is computed individually within the declared interval.

For example:

- A silver medal in the interval 88–92 results in an average score of 89.27.
- A silver medal in the interval 85–95 yields a lower average score of 88.18.

When only one medal category is awarded to a wine (e.g., multiple silvers), the average of that range suffices. However, when multiple categories are involved (e.g., both gold and silver), the initial medal estimates must be adjusted based on the distribution of higher- and lower-ranked awards.

To correct for the informational imbalance between different categories, the method performs a value shift:

$$g_x^1 = g_x^0 - (G_{\mathrm{avg}} - S_{\mathrm{avg}}) \times \left(\frac{G_{\mathrm{avg}} - G_{\min}}{G_{\max} * G_{\min}}\right) \times \left(\frac{|S|}{|G| + |S|}\right) - (G_{\mathrm{avg}} - G_{\min} + B_{\max} - B_{\mathrm{avg}}) \times \left(\frac{G_{\mathrm{avg}} - G_{\min}}{G_{\max} * G_{\min}}\right) \times \left(\frac{|B|}{|G| + |B|}\right)$$

$$s_x^1 = s_x^0 + (G_{\mathrm{avg}} - S_{\mathrm{avg}}) \times \left(\frac{S_{\max} - S_{\mathrm{avg}}}{S_{\max} * S_{\min}}\right) \times \left(\frac{|G|}{|G| + |S|}\right) - (S_{\mathrm{avg}} - B_{\mathrm{avg}}) \times \left(\frac{S_{\mathrm{avg}} - S_{\min}}{S_{\max} * S_{\min}}\right) \times \left(\frac{|B|}{|S| + |B|}\right)$$

$$b_x^1 = b_x^0 + (S_{\mathrm{avg}} - B_{\mathrm{avg}}) \times \left(\frac{B_{\max} - B_{\mathrm{avg}}}{B_{\max} * B_{\min}}\right) \times \left(\frac{|S|}{|B| + |S|}\right) + (G_{\mathrm{avg}} - G_{\min} + B_{\max} - B_{\mathrm{avg}}) \times \left(\frac{B_{\max} - B_{\mathrm{avg}}}{B_{\max} * B_{\min}}\right) \times \left(\frac{|G|}{|G| + |B|}\right)$$

Where:

- X_{avg} is the arithmetic average of all scores for the respective award,
- |X| — the number of awards in this category.

This adjustment ensures that the presence of higher-level awards shifts the center of gravity upward, and vice versa. For competitions that already report numeric scores, this transformation is skipped, and raw values are used.

4.1.5. Competition weighting and aggregation

Each competition is assigned a prestige coefficient (Pc) based on its perceived rigor, global visibility, historical consistency, and rate of medal inflation. This coefficient is used to weight each medal's contribution to the wine's final score.

For each wine, all adjusted medals received across different competitions are aggregated (3).

$$R = \frac{\sum_{i=1}^{M} r_i \cdot Pc_i}{\sum_{j=1}^{M} Pc_j} \qquad (3)$$

Where:

- M is the total number of medals awarded to the wine,
- r_i is the adjusted score of medal,
- Pc_i is the competition coefficient for that medal.

This method ensures that wines with high-value medals from prestigious competitions are scored higher, while overrepresentation from inflated or opaque competitions does not distort the final rating.

4.1.6. Normalization

Final scores are rescaled to the sum of Pc from all the medals.

– If the $\sum Pc$ is lower than a certain level of credibility (if the awards come from a few smaller competitions) - the GWMR rating is slightly decreased,
– If the $\sum Pc$ is higher than a certain level of credibility (multiple medals come from prestigious big competitions) - the GWMR rating is slightly increased.

4.2. Vivino and GWMR Correlation

To understand the relationship between Vivino ratings and the GWMR (Global Wine Medal Rating), two correlation measures were evaluated: **Pearson correlation** and **Chatterjee's Xi coefficient**.

– Pearson correlation quantifies the strength and direction of a linear relationship between two continuous variables, ranging from -1 (perfect negative linear correlation) to +1 (perfect positive linear correlation).
– Chatterjee's Xi is a more recent, nonparametric measure of association that captures any kind of dependence, not just linear. It ranges from 0 (no dependence) to 1 (complete dependence), and is particularly useful for detecting monotonic or nonlinear relationships.

After comparing both, it was chosen to proceed with **Pearson correlation** as the relationship between Vivino ratings and GWMR appears approximately linear based on visual inspection of scatter plots and fitted regression lines.

5. Results

The results presented in this chapter are derived from an ongoing data mining and statistical modeling project conducted in partnership with Corina Besliu and Vivino platform.

5.1. GWMR Statistics and Distributional Patterns

5.1.1. General picture

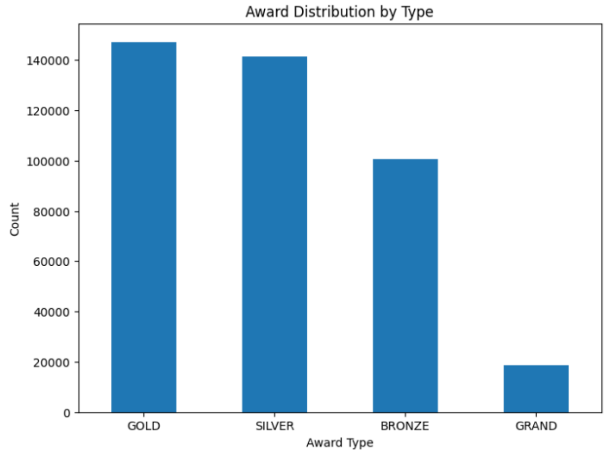

Figure 2. Distribution of Award Types Across the Full GWMR Dataset

Figure 2 provides a foundational overview of the total volume of awards by type within the Global Wine Medal Rating (GWMR) dataset. It reveals that gold and silver medals dominate the distribution, with each category accounting for over 140,000 awards, followed by a significantly lower number of bronze medals and a relatively rare allocation of grand gold. The structure reflects prevailing trends in international wine competitions, where the inflation of top-tier awards—especially gold—has become a recognized phenomenon. This inflation may be driven by marketing incentives, differing jury standards, or variation in award thresholds across events. The relative scarcity of grand gold medals underscores their perceived exclusivity and validates their continued statistical and reputational weight. As a first step in the broader analysis, this distribution sets the stage for deeper exploration into how medal types are allocated across vintages, countries, wine styles, and consumer-perceived quality.

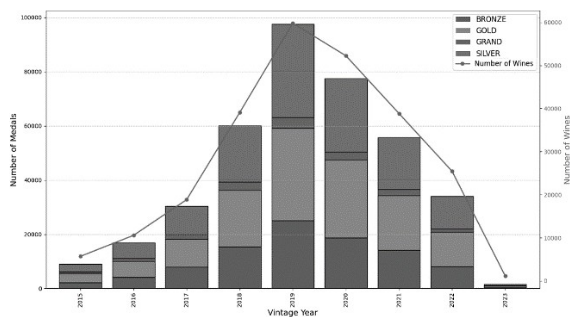

Figure 3. Distribution of Medals and Awarded Wines by Vintage Year

Figure 3 presents the distribution of awarded medals across vintage years, segmented by medal tier (bronze, silver, gold, grand gold), alongside the total number of wines that received at least one award (red line, right axis). The data reveal a clear peak in awarded wines for the 2019 vintage, which also dominates in total medal volume across all categories. The decline in awarded wines and medal counts for more recent vintages likely reflects the typical lag in wine competition participation: younger vintages often enter competitions in lower numbers due to aging requirements or delayed market releases. Medal composition appears relatively stable, with gold and silver medals constituting the majority share over time. Early vintages (2015–2017) show a narrower medal base, which may be due to fewer wines remaining in competitive circulation.

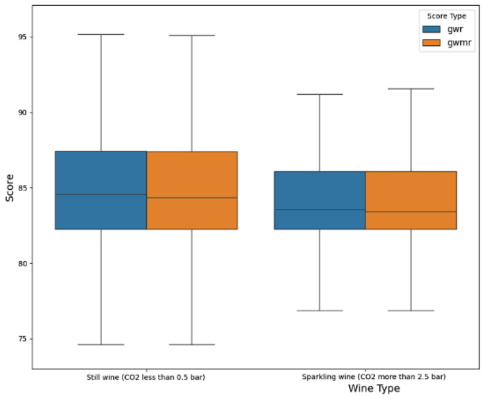

Figure 4. Score Distribution of GWR and GWMR Across Still and Sparkling Wine

Figure 4 compares the distribution of scores assigned by the Global Wine Rating (GWR) and the Global Wine Medal Rating (GWMR) systems across two major wine types: still wines and sparkling wines. Notably, the median scores for both scoring systems are closely aligned within each wine category, reflecting a consistent threshold of evaluation between the two methodologies. This alignment underscores the internal calibration of GWR and GWMR, despite their differing sources— consumer-based ratings for GWR and aggregated professional competition results for GWMR. The interquartile ranges are also similar, although slightly wider for still wines, indicating broader variability in that category.

5.1.2. Country comparison

Figure 5 presents the proportion of gold and grand medals relative to all awarded medals, aggregated by country over the 2020–2024 period. The data reveal substantial heterogeneity in high-level award concentration across producing countries. Germany leads the ranking with over 60% of its medals being gold or grand gold, followed by Hungary and Slovakia — both surpassing the 50% mark. This suggests a notable degree of selectivity or competitive strength in the wines these countries submit to international competitions. Central and Eastern European countries (e.g., Czech Republic, Moldova, Romania) consistently exhibit high gold ratios, potentially reflecting targeted participation in competitions where their wine styles are highly valued or fewer but higher-quality entries are submitted. By contrast, traditional heavyweights like Italy, Spain, and France report relatively moderate ratios, possibly due to a larger volume and diversity of entries, including mid- tier wines. Toward the lower end of the spectrum, the United Kingdom, Canada, and New Zealand demonstrate significantly lower gold medal ratios, which may reflect either a broader range of submitted quality tiers or less favorable alignment with jury expectations.

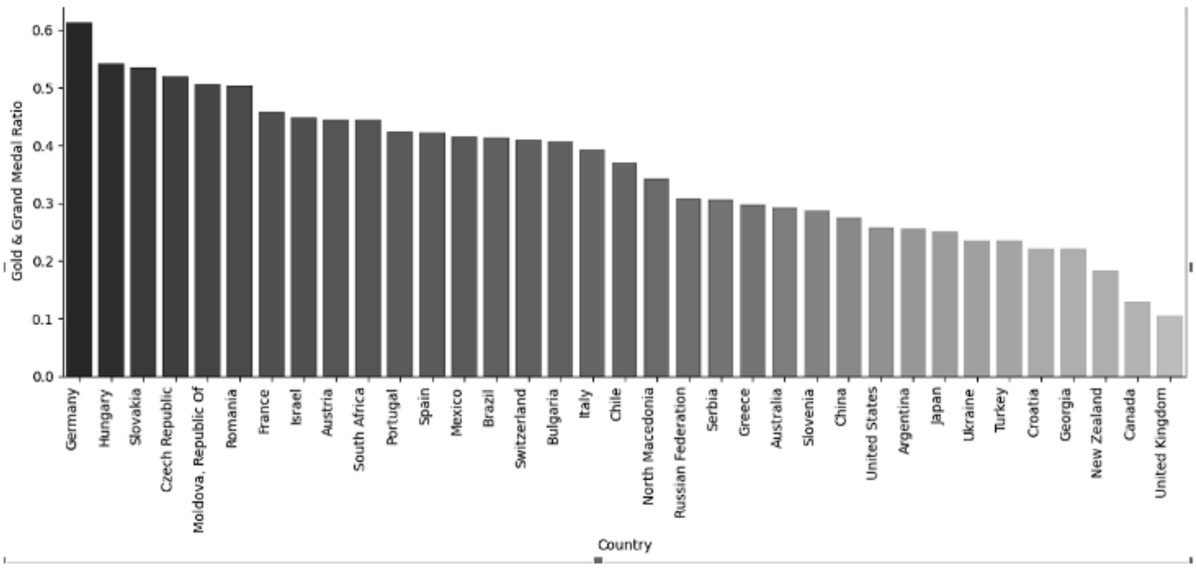

Figure 5. Gold & Grand Medal Ratio per Country

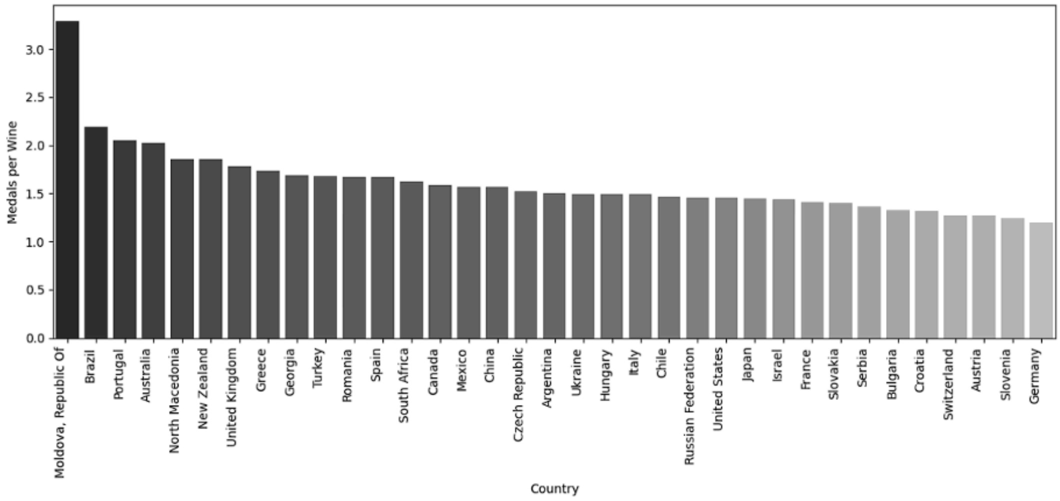

Figure 6. Average Number of Medals per Wine by Country

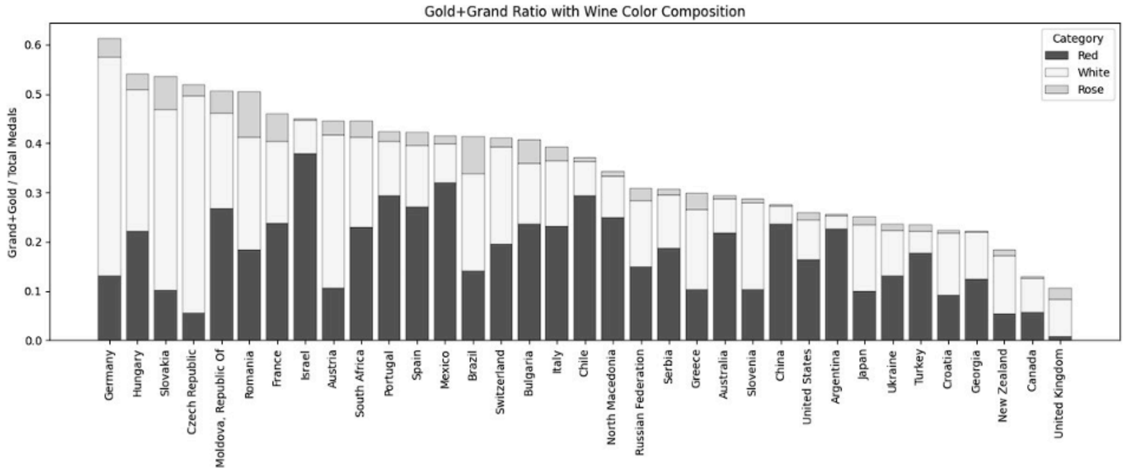

Figure 7. Gold & Grand Medal Share by Country with Wine Color Composition

Figure 6 shows the average number of medals received per wine by country, offering a view into how frequently wines from each region are awarded in international competitions. Moldova stands out prominently with over three medals per wine—far ahead of all other countries—suggesting a high concentration of multi-awarded wines, potentially due to repeated entries of standout labels or targeted medal-optimization strategies. Brazil, Portugal, and Australia also show strong medal density, indicating either high award rates or frequent re-entry of the same wines across different contests. Conversely, established wine-producing nations such as Germany, France, and Italy fall on the lower end of the distribution, which may reflect broader portfolio diversity, a focus on fewer competitions, or less strategic targeting of repeat entries. This metric is useful for understanding national trends in medal accumulation efficiency, independent of sheer volume of submissions.

Figure 7 reveals that different countries achieve their top awards with notably different profiles. For instance, Germany and Hungary achieve much of their high medal performance through white wines, whereas Italy, Chile, and Argentina owe their success predominantly to red wine entries. Interestingly, countries like France and Spain display more balanced contributions across both red and white, suggesting a broader stylistic range at medal-winning quality. Rosé wines, though generally less dominant, show up significantly in a few countries such as Austria and Portugal, hinting at specialized regional strengths.

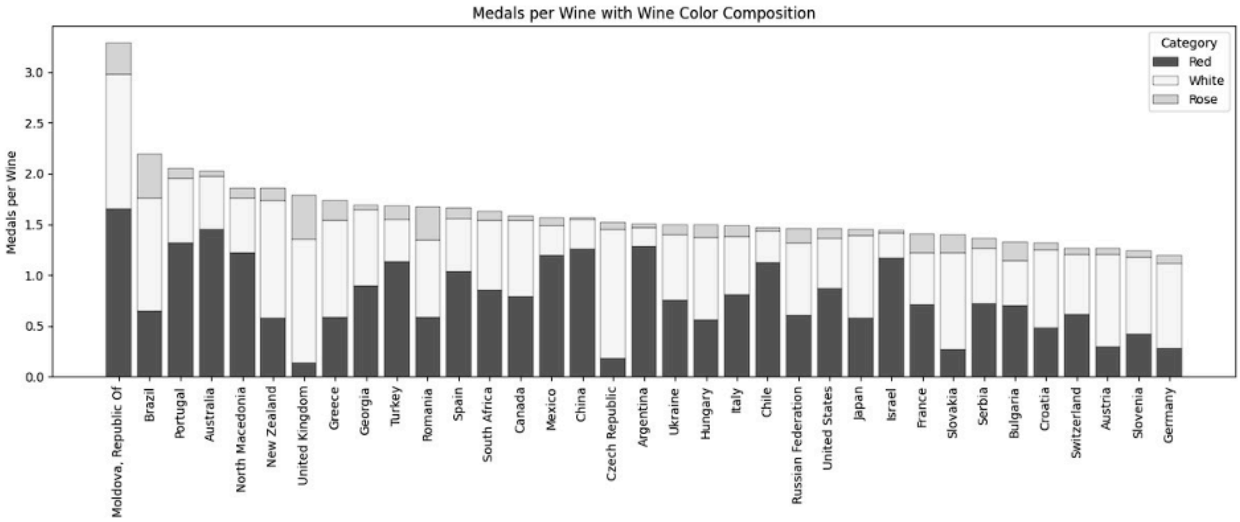

Figure 8. Average Number of Medals per Wine by Country and Color Composition

Figure 8 builds upon the previous medal density analysis by disaggregating average medals per wine by wine color (red, white, rosé). While overall medal intensity is familiar, the compositional insights reveal interesting disparities between submission volume and award-tier success by color.

A few examples:

- France's rosé wines, while only 10% of total awarded entries, account for 17% of its top-tier gold and grand awards—indicating a performance surplus.
- Similarly, Romania shows a dramatic overperformance in rosé, rising from 19% of general awards to 35% among gold/grand awards.
- Conversely, Austria's red wines, though making up 23% of its medals, only contribute 17% of top-tier awards, suggesting relative underperformance.
- Greece's white wines consistently overachieve, growing from 52% of general awards to 60% of gold-tier outcomes.
- Meanwhile, the U.S. maintains a dominant red wine profile, with red wines gaining even more share in high-value awards.
- Germany displays near-perfect proportionality across categories, reinforcing the precision of its selection and competition alignment.

5.2. Comparative Analysis: GWMR vs. Vivino Ratings

Table 1. Country correlation between Vivino and GWMR rating

Country	Pearson	Xi
South Africa	0.38	0.36
Moldova	0.33	0.16
Greece	0.3	0.28
United Kingrom	0.3	0.31
Hungary	0.3	0.29
Chile	0.26	0.26
Turkey	0.25	0.26
Argentina	0.24	0.24
Australia	0.23	0.32
Austria	0.22	0.24
Germany	0.22	0.28
Spain	0.2	0.30
…	…	…
Portugal	0.19	0.23
France	0.18	0.49
Romania	0.18	0.25
New Zealand	0.15	0.26
USA	0.14	0.38
Switzerland	0.13	0.48
Georgia	0.025	0.17

For further analysis the top 5 and bottom 5 countries were chosen according to the Pearson coefficient. Other aspects will be analyzed, like matches and mismatches between GWMR and Vivino ratings.

5.2.1. Top 3 countries by correlation

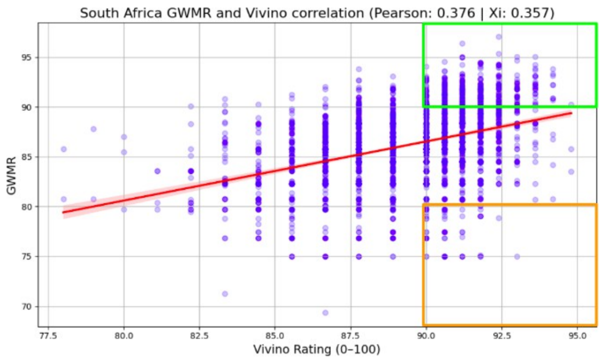

Figure 9. South Africa GWMR and Vivino correlation

- The data points in the green (upper-right) rectangle represent elite wines where both vivino and GWMR ratings are high. (both>90),
- The orange (lower-right) rectangle represents discrepant wines that received a high rating based on vivino, but were less successful at competitions (Vivino>90 but GWMR<80).

Table 2. Details on correlations and exceptions for South Africa

Wine color	Discrepant wines count	Elite wines count	Total count	Discrepant wines %	Elite wines %
Red	21	163	1218	1.72	13.38
White	15	115	955	1.57	12.04
Rose	1	3	89	1.12	3.37

When examining highly rated wines, the proportion of elite wines—those receiving high scores from both Vivino users and GWMR (both > 90)—significantly exceeds that of discrepant wines, which score highly on Vivino but underperform in competitions (Vivino > 90, GWMR < 80).

For example, among red wines, 13.4% are elite compared to only 1.7% discrepant. This pattern holds for white wines as well, with 12.0% elite versus 1.6% discrepant. Rosé wines show a similar trend, though with smaller sample sizes.

These findings suggest that high Vivino scores often align with strong competition results, reinforcing the reliability of user-generated ratings for identifying standout wines.

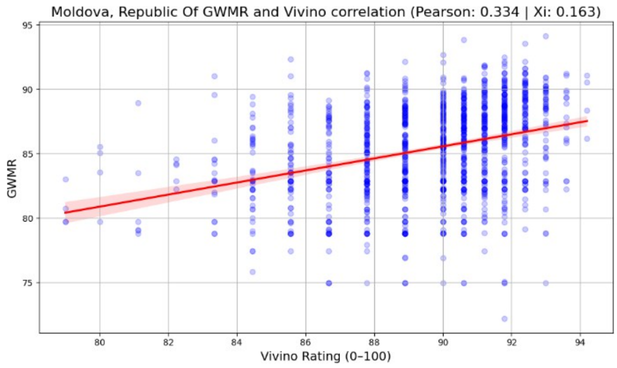

Figure 10. Moldova GWMR and Vivino correlation

Table 3. Details on correlations and exceptions for Moldova

Wine color	Discrepant wines count	Elite wines count	Total count	Discrepant wines %	Elite wines %
Red	13	41	587	2.21	6.98
White	10	25	509	1.96	4.91
Rose	4	5	141	2.84	3.55

In Moldova elite wines (Vivino > 90 and GWMR > 90) consistently outnumber discrepant wines (Vivino > 90 and GWMR < 80), though the margins are smaller than in the previous case.

While Vivino ratings still correlate moderately with competition performance, the lower elite percentages suggest a weaker alignment between user perception and expert assessment.

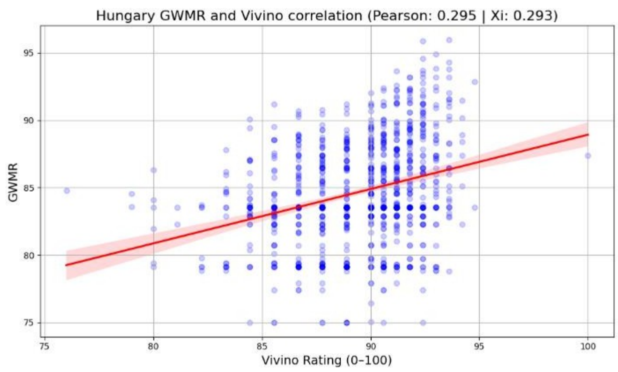

Figure 11. Hungary GWMR and Vivino correlation

Table 4. Details on correlations and exceptions for Hungary.

Wine color	Discrepant wines count	Elite wines count	Total count	Discrepant wines %	Elite wines %
Red	21	16	384	5.47	4.17
White	1	0	71	1.41	0.00
Rose	25	55	536	4.66	10.26

5.2.2. Countries with lowest correlation

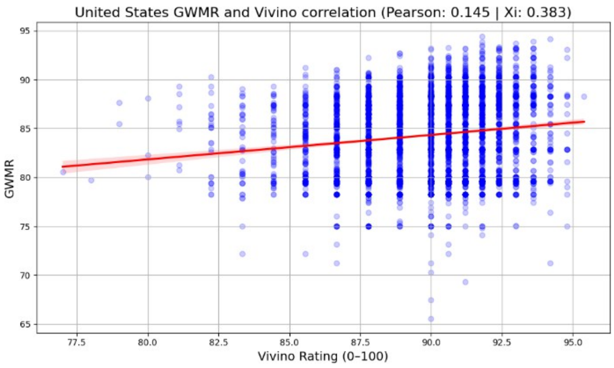

Figure 12. USA GWMR and Vivino correlation

Table 5. Details on correlations and exceptions for USA.

Wine color	Discrepant wines count	Elite wines count	Total count	Discrepant wines %	Elite wines %
Red	311	183	3021	10.29	6.06
White	78	58	1340	5.82	4.33
Rose	9	5	178	5.06	2.81

In the USA there is a clear tendency for Vivino users to overrate wines, especially red wines, compared to GWMR awards:

– Red wines exhibit a high discrepancy rate of 10.3%, far exceeding their elite rate of 6.1%, indicating many reds are popular with consumers but underperform in competitions.
– White wines show a similar pattern, though less extreme, with 5.8% discrepant versus 4.3% elite.
– Rosé wines follow the same trend, though their share in the dataset is smaller.

This suggests that in the U.S., consumer ratings (Vivino) frequently diverge from formal recognition (GWMR), with red wines particularly benefiting from consumer favor.

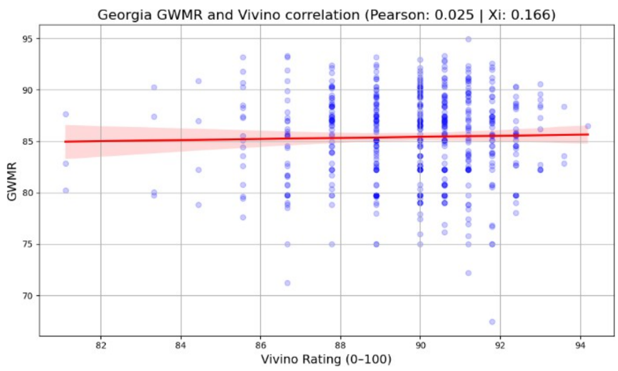

Figure 13. Georgia GWMR and Vivino correlation

Table 6. Details on correlations and exceptions for Georgia.

Wine color	Discrepant wines count	Elite wines count	Total count	Discrepant wines %	Elite wines %
Red	11	21	278	3.96	7.55
White	3	0	20	15.00	0.00
Rose	16	10	217	7.37	4.61

In Georgia, the data reveals a noticeable divergence between consumer and expert-derived assessments, especially for white and rosé wines:

– White wines have the highest discrepancy rate at 7.4%, while elite wines are only 4.6% — suggesting that consumer enthusiasm is not always matched by award recognition.
– Rosé wines stand out: 15% are discrepant and none are elite, though the total sample is small (n = 20), so caution is needed.
– Red wines perform more consistently, with 3.96% discrepant and 7.55% elite, indicating a relatively stronger alignment between Vivino scores and competition outcomes.

5.2.3. Regional comparison

Table 7. Region Correlation between Vivino and GWMR rating.

Region	Pearson	Xi
Coastal Region (South Africa)	0.38	0.31
Burgundy (France)	0.32	0.38
Central Valley (Chile)	0.31	0.21
Veneto (Italy)	0.27	0.22
Mendoza (Argentina)	0.25	0.21
La Rioja (Spain)	0.24	0.24
Douro (Portugal)	0.24	0.18
Castile-La Mancha (Spain)	0.23	0.17
South Australia (Australia)	0.21	0.27
Catalonia (Spain)	0.21	0.2
Abruzzo (Italy)	0.2	0.15
Toscana (Italy)	0.2	0.23
...	...	...
Piedmont (Italy)	0.18	0.31
Castile and Leon (Spain)	0.17	0.18
Rhone Valley (France)	0.17	0.2
Valencia (Spain)	0.17	0.14
Rhineland-Palatinate (Germany)	0.17	0.32
Alsace & Lorraine (France)	0.16	0.25
Bordeaux (France)	0.16	0.37

Sicilia (Italy)	0.16	0.13
Marlborough (New Zealand)	0.16	0.23
California (United States)	0.15	0.34
Valais (Switzerland)	0.14	0.36
South West France (France)	0.13	0.15
Provence (France)	0.11	0.22
Alentejo (Portugal)	0.11	0.12
Loire Valley (France)	0.1	0.28
Puglia (Italy)	0.1	0.16
Lisboa (Portugal)	0.035	0.061

The correlation table between Vivino user ratings and GWMR scores across 30 wine regions reveals a generally low to moderate alignment, with Pearson coefficients rarely exceeding 0.38. Notably, regions such as the Coastal Region of South Africa, Burgundy (France), and Central Valley (Chile) exhibit the highest correlations, suggesting a closer convergence between consumer preferences and expert-driven evaluations in these markets. Conversely, major traditional regions like Bordeaux, Piedmont, and Tuscany show only modest correlations, highlighting persistent gaps between crowd-sourced appreciation and institutional recognition. These discrepancies underline the nuanced and region-specific nature of wine perception, reinforcing the value of multidimensional rating systems like GWR that aim to bridge the gap between public sentiment and professional standards.

6. Discussions

This study reveals both convergence and divergence in how wine quality is perceived by consumers (via Vivino) and by professional juries (via the GWMR). These discrepancies are rooted in fundamentally different evaluation logics. Vivino scores are subjective, often influenced by situational, emotional, or aesthetic factors

— including label design, occasion of consumption, or brand loyalty. In contrast, medals awarded in professional competitions derive from blind tastings under controlled conditions, aiming for objectivity and consensus across expert panels. The relative alignment or mismatch between these two logics is not a flaw but an opportunity to understand how different segments of the market perceive wine quality.

The varying correlation levels observed across countries and wine types underscore the influence of local wine culture, jury standards, and strategic behavior by producers. For instance, countries like Germany and Hungary exhibit high gold-to-total medal ratios and stronger alignment between GWMR and Vivino scores, suggesting coherent internal standards. In contrast, markets like the United States show substantial consumer enthusiasm (high Vivino scores) for wines that underperform in competitions, indicating a more sentiment-driven, brand-influenced perception of quality.

Another consideration is the role of volume and visibility. Vivino's user-generated content benefits from network effects, where popular wines gain more visibility and further ratings. In contrast, medals are less visible post-award unless proactively marketed by producers. This asymmetry in visibility and crowd amplification may explain some of the persistent differences in score alignment.

From a market perspective, medals may serve as long-term signals of investment-grade quality (especially in regions like Burgundy), whereas Vivino ratings often reflect immediate drinkability and popularity. The GWMR provides a stabilizing reference point by aggregating across competitions and adjusting for medal inflation, helping bridge this temporal and perceptual gap.

Finally, this dual analysis reveals potential crowd biases in both systems. Vivino users may cluster toward familiar brands or varietals, while competition juries may favor traditional styles. The GWR composite score—combining both—can be seen as a tool for reconciling these biases and offering a more holistic measure of quality perception across audiences.

7. Conclusion

This study introduces a novel comparative framework for understanding wine quality by combining two forms of crowdsourced evaluation: consumer ratings from Vivino and professional peer assessments via the Global Wine Medal Rating (GWMR). Using a harmonized dataset of over 85,000 wines, we demonstrate that while these systems are built on divergent assumptions and logics, they often converge in identifying elite performers—particularly in countries with coherent quality standards and effective medal targeting strategies.

Our findings confirm that both consumer-driven and expert-mediated systems offer valid and valuable information, though each reflects different priorities and use cases. Vivino serves as a proxy for real-time, consumption-based preferences, while GWMR consolidates the delayed but institutional credibility of formal accolades. When combined, these systems enable a more nuanced and multi-dimensional understanding of wine quality, especially through the hybrid GWR score.

From a theoretical standpoint, this work extends the literature on hedonic pricing, rating standardization, and market signaling by incorporating competition medals into the academic discourse—an area previously underexplored. Practically, the results can inform producers, retailers, and consumers seeking more integrated and reliable tools for wine evaluation.

Future research should expand this framework by including expert critic ratings, integrating price data into hedonic models, and exploring temporal dynamics—such as how Vivino and GWMR scores evolve over time. The development of real-time recommendation engines and hybrid scoring systems, grounded in cross-source validation, represents a promising direction for both academia and industry.

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