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Integrating Human Resource Analytics into Accounting-Based Decision-Making: Evidence on Financial Performance and Competitive Capability

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Abstract
Purpose: This study examines how human resource (HR) analytics adoption relates to perceived organizational financial performance in Armenia and assesses evidence-based management and accounting integration as explanatory mechanisms. Design/methodology/approach: The original cross-sectional study surveyed 287 HR managers, financial executives, and senior managers from organizations operating in Armenia (287 of 350 questionnaires; reported response rate: 82.0%). The questionnaire measured HR analytics adoption, evidence-based management, accounting integration, and perceived financial performance. Reported results were obtained using partial least squares structural equation modeling (PLS-SEM), bootstrapped mediation analyses, and industry comparisons. Findings: The source manuscript reports positive associations between HR analytics adoption and perceived financial performance ($\beta = 0.42$, $p < 0.001$), evidence-based management ($\beta = 0.58$, $p < 0.001$), and accounting integration ($\beta = 0.61$, $p < 0.001$). Reported indirect effects through evidence-based management ($\beta = 0.27$), accounting integration ($\beta = 0.21$), and their sequential pathway ($\beta = 0.08$) were statistically significant. Analytical skills shortages (mean = 4.12) and data-quality/integration problems (mean = 4.05) were leading reported implementation barriers. Originality/value: The article develops an HR–accounting integration perspective and situates it within Armenian organizations. The findings concern survey-based perceptions rather than audited financial results. Because respondent-level data were unavailable for independent re-estimation, some inconsistencies in the originally reported joint-model statistics remain to be resolved before submission.
Keywords: human resource analytics; accounting integration; evidence-based management; perceived financial performance; PLS-SEM; competitive advantage

1. Introduction
Organizations increasingly seek to integrate workforce intelligence with financial planning, cost control, and strategic resource allocation. Human resource analytics (HRA) refers to the systematic use of workforce-related data and analytical methods to inform organizational decisions; its promise extends beyond descriptive headcount metrics to the evaluation of human capital investments. Nevertheless, the link between analytical capability and measurable economic outcomes remains contingent on the quality of data, organizational decision processes, and the ability to act on evidence (Marler & Boudreau, 2017; Minbaeva, 2018; Tursunbayeva et al., 2018; Caughlin, 2018; Usman et al., 2024).

An unresolved management problem concerns the boundary between HR dashboards and accounting-based decisions. Recruitment, learning, absenteeism, turnover, and workforce planning have direct budgetary implications, yet organizations frequently manage HR and finance information in separate systems. Integration can make personnel expenditures and expected workforce benefits visible within budgeting, variance analysis, and investment appraisal. It does not, however, automatically establish that analytics causes higher profitability: financial outcomes are also influenced by market structure, management quality, technology, and sector-specific conditions (Angrave et al., 2016; Mohamed & Shehata, 2023; Badhon et al., 2024).

The Armenian organizational setting provides a relevant context for exploring how emerging analytical practices interact with financial management. The source manuscript situates the research against digital transformation activity in Armenia, including the development of AI-supported financial controls in public

administration (Mnatsakanyan & Smbatyan, 2025; Damnjanović et al., 2025). Evidence about private-sector HR–accounting integration in this setting is comparatively limited. This manuscript therefore focuses on the distinct roles of analytical adoption, evidence-based management, and accounting integration instead of treating HR analytics as a single technology investment.

The research addresses four questions: (RQ1) Is HRA adoption positively associated with perceived organizational financial performance? (RQ2) Does evidence-based management account for part of this association? (RQ3) Is the relationship also transmitted through accounting integration, including a sequential pathway from evidence-based management? and (RQ4) Which implementation obstacles and sectoral differences emerge among sampled organizations? The contribution is a theoretically grounded interpretation of the original survey findings, preserving all eight empirical tables and the original structural figure while specifying the limits of cross-sectional, self-reported evidence.

2. Literature Review and Hypothesis Development

2.1. Human resource analytics as an organizational capability

HRA encompasses the collection, integration, analysis, and interpretation of employee-related information for managerial action. A distinction must be drawn between data availability and analytical competence: reports alone produce limited value unless their definitions are credible, analyses are interpretable, and findings influence action. Minbaeva conceptualizes credible human capital analytics as involving data quality, analytical capability, and strategic ability to act, a combination that helps explain why investments in HR technology have heterogeneous outcomes (Minbaeva, 2018). Empirical and conceptual reviews similarly caution against equating adoption with realized strategic value (Marler & Boudreau, 2017; Angrave et al., 2016).

2.2. Resource-based view and human capital investment

The resource-based view proposes that enduring advantages may arise from firm resources and capabilities that are valuable and difficult to imitate (Barney, 1991; Donthu, 2024). In this framework, HRA itself is unlikely to confer durable advantage merely because a software package has been purchased. Its strategic potential is better understood as a socially embedded capability combining skilled employees, data governance, managerial routines, and cross-functional coordination. The accounting function contributes by connecting human capital decisions to cost and performance consequences; the resulting routines may be more difficult to replicate than an analytics dashboard alone (Minbaeva, 2018; Mohamed & Shehata, 2023).

2.3. Evidence-based management as a mediating mechanism

Evidence-based management (EBM) is the use of systematically assessed information to guide organizational decisions. Analytics can inform managerial judgment by making patterns in recruitment, retention, capability development, and personnel spending more visible. Yet interpretation and implementation depend on how managers evaluate evidence, discuss uncertainty, and account for contextual considerations. Prior research links HR analytics, EBM, and organizational performance, although the robustness and generalizability of empirical findings remain open to investigation (Mushtaq et al., 2024; Marler & Boudreau, 2017; Sharma et al., 2022).

2.4. Accounting integration as a decision-making mechanism

Accounting integration (AI) is defined here as the extent to which workforce analytics enters financial planning and evaluation processes such as human capital cost analysis, workforce return-on-investment assessments, and financial appraisal of HR initiatives. The proposed mechanism is informational and procedural: integrated data can improve the comparability of alternatives, inform cost forecasts, and align operating decisions with expenditure constraints. Because the study uses perceptual responses rather than audited accounting records, the conceptual mechanism is tested at the level of managers' reported practices and outcomes, not through demonstrated changes in profit or cash flow (Ali, 2025; Mohamed & Shehata, 2023; Siddiqua et al., 2023).

2.5. Proposed hypotheses and conceptual pathways

The original model specifies six direct associations: H1, HRA adoption is positively related to perceived organizational financial performance (OFP); H2, HRA adoption is positively related to EBM; H3, EBM is positively related to OFP; H4, HRA adoption is positively related to AI; H5, AI is positively related to OFP; and H6, EBM is positively related to AI. Three mediated relationships are also examined: HRA → EBM → OFP, HRA → AI → OFP, and HRA → EBM → AI → OFP. These hypotheses are associational because the measurement design does not identify temporal ordering or eliminate rival explanations.

3. Research Methodology

3.1. Study design and setting

The study employed a cross-sectional questionnaire design targeting personnel who could comment on workforce analytics and financial decision processes in Armenian organizations. The original manuscript describes a quantitative approach analyzed through SPSS 26 and SmartPLS 3.3. A cross-sectional survey is suitable for examining patterns of association but cannot establish the causal effects of HRA adoption, EBM, or AI on financial outcomes (Podsakoff et al., 2003; Hair et al., 2019).

3.2. Target population, sampling, and data collection

Eligible respondents were HR managers, financial executives, and senior management personnel working in organizations where HR analytics had been deployed. The source describes industry-stratified random sampling across financial services, information technology, manufacturing, professional services, and other services. A total of 350 questionnaires were distributed and 287 completed surveys were returned, yielding 287/350 = 82.0%. Details of the complete sampling frame, recruitment dates, company count, number of participants per company, exclusion criteria, and nonresponse analysis were not available in the supplied manuscript; consequently, the sampling procedure cannot be independently verified from the article alone.

3.3. Measures and operational definitions

All substantive items were described as five-point Likert-type responses (1 = strongly disagree to 5 = strongly agree). The four focal constructs were HRA adoption (12 items covering recruitment, performance, retention, and workforce planning analytics), EBM (8 items), AI (10 items), and OFP (8 items). OFP represents perceived profitability, revenue growth, cost efficiency, and return on investment—not financial statement data. The source reports expert review by five academics and three practitioners and a pilot test involving 35 participants. The full wording of the 38 scale items was not supplied; a reproducible journal submission should append the instrument and document adaptation and translation procedures, if relevant.

3.4. Reliability and validity assessment

The original document reports Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), indicator loadings, and the Fornell–Larcker matrix. These are standard components of reflective measurement evaluation (Fornell & Larcker, 1981; Hair et al., 2019). A full contemporary assessment should also report item-level loadings, heterotrait–monotrait (HTMT) ratios, cross-loadings as relevant, and construct specifications; HTMT provides an important additional diagnostic because the Fornell–Larcker criterion may fail to detect some discriminant-validity problems (Henseler et al., 2015).

3.5. Structural analysis, mediation, and subgroup comparison

The supplied analysis used PLS-SEM and stated that 5,000 bootstrap resamples were drawn to assess direct and indirect effects. Structural results include estimated path coefficients, t statistics, reported p values, and explained variance. Industry comparisons were also reported. When full data become available, model collinearity (variance inflation factors), confidence intervals for all paths, effect sizes, predictive performance, and measurement invariance before multi-group comparisons should be assessed and reported consistently (Hair et al., 2019). The tables below are preserved from the original document; no unreported estimates have been inferred.

3.6. Research ethics and reproducibility

According to the original manuscript, institutional ethics approval and participant informed consent were obtained, confidentiality was assured, and participation was voluntary. The approving institution and approval number were not included in the source. Before submission, the authors should provide the relevant approval details, a data availability statement aligned with participant consent, information about organizational recruitment, and the survey instrument. No respondent-level data or SmartPLS output files accompanied the manuscript, so independent statistical replication was not possible.

4. Results

4.1. Respondent and organizational characteristics

Table 1 describes the 287 respondents. Medium-sized organizations accounted for 42.5% of the sample, compared with 35.2% from large organizations and 22.3% from small organizations. Financial services (28.6%) and information technology (24.4%) were the largest reported industry groups. Nearly half of the respondents occupied HR management positions (49.5%). The table describes the sample, not the population distribution of Armenian organizations.

Table 1. Respondent and organization characteristics (N = 287)

Characteristic	Category	Frequency	Percentage
Organization Size	Small (< 100 employees)	64	22.3%
	Medium (100-499 employees)	122	42.5%
	Large (≥ 500 employees)	101	35.2%
Industry Sector	Financial Services	82	28.6%
	Information Technology	70	24.4%
	Manufacturing	56	19.5%
	Professional Services	44	15.3%
	Other	35	12.2%
HR Analytics Experience	< 2 years	89	31.0%
	2-5 years	134	46.7%
	> 5 years	64	22.3%
Respondent Position	HR Manager	142	49.5%
	Financial Executive	87	30.3%
	Senior Management	58	20.2%

Source: original survey summary supplied by the author. Percentages are reported to one decimal place.

4.2. Descriptive statistics

Mean scores were above the scale midpoint for all four constructs, with adoption (M = 3.72) exceeding EBM (M = 3.58), AI (M = 3.41), and OFP (M = 3.65). The descriptive results are consistent with moderate-to-high levels of reported activity among the sampled respondents; they do not reveal actual adoption prevalence in the wider economy.

Table 2. Descriptive statistics for the focal constructs

Variable	Mean	SD	Skewness	Kurtosis
HR Analytics Adoption	3.72	0.84	-0.42	-0.31
Evidence-Based Management	3.58	0.79	-0.38	-0.28
Accounting Integration	3.41	0.91	-0.29	-0.45
Organizational Financial Performance	3.65	0.86	-0.35	-0.22

Note: SD = standard deviation. Values reproduced from the supplied manuscript.

4.3. Measurement model

The reported internal consistency estimates were α = 0.89 (HRA), 0.86 (EBM), 0.84 (AI), and 0.91 (OFP). Table 3 reports CR values from 0.91 to 0.95 and AVE values from 0.56 to 0.68. These results generally suggest acceptable reliability and convergent validity on common reporting criteria. The original narrative states that two items loaded at 0.69, but the table provides only construct-level ranges, so item-level verification is still required. Table 4 contains the reported Fornell–Larcker matrix; because HTMT is not reported, discriminant validity should be regarded as provisionally rather than comprehensively assessed (Hair et al., 2019; Henseler et al., 2015).

Table 3. Reported reflective measurement-model results

Construct	Items	Factor Loadings	CR	AVE
HR Analytics Adoption	HRA1-HRA12	0.71-0.89	0.94	0.62
Evidence-Based Management	EBM1-EBM8	0.74-0.87	0.92	0.59
Accounting Integration	AI1-AI10	0.69-0.85	0.91	0.56
Organizational Financial Performance	OFP1-OFP8	0.76-0.91	0.95	0.68

CR = composite reliability; AVE = average variance extracted. Indicator ranges are reproduced, not independently recomputed.

Table 4. Reported Fornell–Larcker discriminant-validity matrix

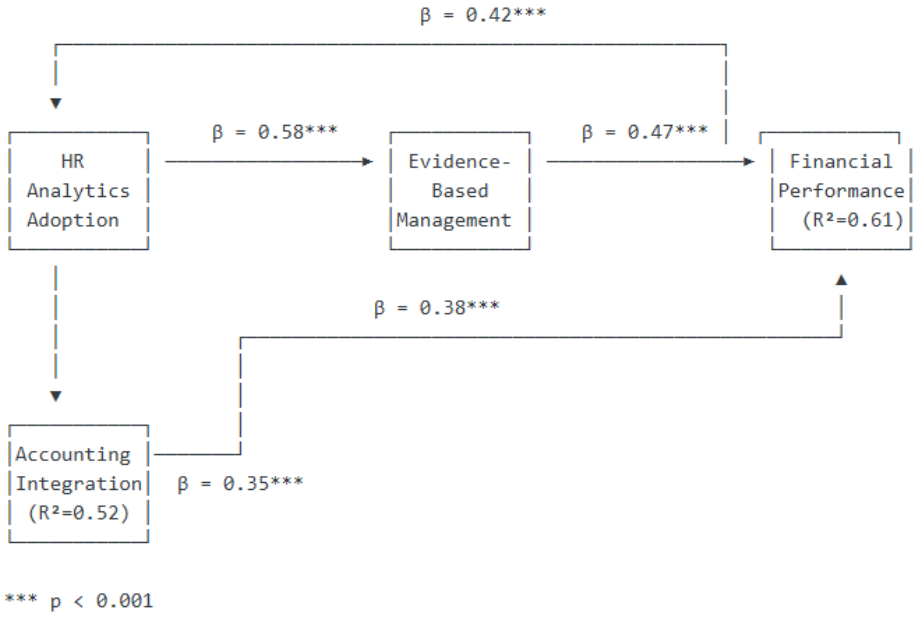
Construct	HRA	EBM	AI	OFP
HR Analytics Adoption (HRA)	0.79			
Evidence-Based Management (EBM)	0.68	0.77		
Accounting Integration (AI)	0.61	0.72	0.75	
Organizational Financial Performance (OFP)	0.59	0.67	0.64	0.82

HRA = HR analytics adoption; EBM = evidence-based management; AI = accounting integration; OFP = perceived organizational financial performance. Diagonal entries are square roots of AVE.

4.4. Structural relationships and explained variance

The source reports statistically significant positive direct paths for all six hypotheses (Table 5). The strongest reported direct coefficient is HRA → AI (β = 0.61), followed by HRA → EBM (β = 0.58). The direct path from HRA to OFP is β = 0.42. The originally reported explained variance is $R^2 = 0.34$ for EBM, $R^2 = 0.52$ for AI, and $R^2 = 0.61$ for OFP. These reported outputs require reconciliation as one jointly estimated standardized model: the coefficient and correlation matrices, when combined algebraically, do not reproduce the stated R^2 values. Consequently, interpretation here is explicitly conditional on validation of the model output and should not be treated as a verified, publication-final estimation.

Figure 1. Original structural model reproduced from the supplied manuscript



Note: Original image retained for source fidelity. Several arrow annotations and reported path/R^2 values require checking against a regenerated SmartPLS model output. *** p < 0.001 is the annotation used in the original figure.

Table 5. Reported structural-model path coefficients

Hypothesis	Path	β	t-value	p-value	Decision
H1	HRA → OFP	0.42	6.84	< 0.001	Supported
H2	HRA → EBM	0.58	9.21	< 0.001	Supported
H3	EBM → OFP	0.47	7.56	< 0.001	Supported
H4	HRA → AI	0.61	10.12	< 0.001	Supported
H5	AI → OFP	0.35	5.43	< 0.001	Supported
H6	EBM → AI	0.38	5.89	< 0.001	Supported

Values are copied from the source; the hypothesis decisions are those reported by the original study, pending model consistency checks.

4.5. Indirect pathways

Table 6 summarizes the source-reported bootstrap indirect effects. The EBM pathway (β = 0.27, 95% CI [0.19, 0.36]) and AI pathway (β = 0.21, 95% CI [0.14, 0.29]) are positive, and the sequential pathway through EBM and AI is also reported as positive (β = 0.08, 95% CI [0.04, 0.13]). These rounded values are arithmetically consistent with multiplication of the displayed direct paths. The manuscript also reports a summed total effect

of 0.98, but the coherence of that standardized total effect with the full correlation matrix and the R^2 estimates cannot be established without access to the original model results. It should therefore be reported only as a source-stated quantity rather than as an independently validated inference.

Table 6. Reported bootstrapped indirect effects

Mediation Path	Indirect Effect	95% CI	t-value	p-value
HRA → EBM → OFP	0.27	0.19, 0.36	5.82	< 0.001
HRA → AI → OFP	0.21	0.14, 0.29	4.67	< 0.001
HRA → EBM → AI → OFP	0.08	0.04, 0.13	3.21	0.001

95% CI = reported 95% confidence interval. The original document does not state the exact method used for confidence-interval computation beyond describing bias-corrected bootstrap intervals.

4.6. Industry comparisons

The reported HRA → OFP coefficients vary across sectors, from 0.51 in financial services to 0.35 in the heterogeneous "other" category (Table 7). Reported pairwise tests indicate differences between financial services and manufacturing ($p = 0.04$) and between financial services and the other-sector group ($p = 0.02$). These are exploratory comparisons: exact measurement-invariance tests, adjustment for multiple comparisons, bootstrap difference confidence intervals, and sector-specific respondent counts within each structural model are not provided. The findings therefore identify potential heterogeneity rather than conclusively establishing sector-specific causal effects.

Table 7. Reported multi-group associations by industry

Industry Sector	β (HRA → OFP)	t-value	Significant Difference
Financial Services	0.51	5.23	Reference Group
Information Technology	0.48	4.89	No ($p = 0.72$)
Manufacturing	0.38	3.67	Yes ($p = 0.04$)
Professional Services	0.44	3.21	No ($p = 0.38$)
Other	0.35	2.54	Yes ($p = 0.02$)

"Significant difference" refers to the comparison reported against financial services; the source does not provide a multiple-testing adjustment or group measurement-invariance results.

4.7. Challenges to implementation

Analytical skill gaps ($M = 4.12$) and data quality/integration problems ($M = 4.05$) were the highest-rated barriers, followed by resistance to data-driven organizational culture ($M = 3.89$). Privacy and ethical concerns also appeared among the reported challenges ($M = 3.68$). These are rankings of survey ratings rather than estimates of how frequently each barrier occurs across all Armenian organizations.

Table 8. Reported challenges in integrating HR analytics with accounting

Challenge	Mean	SD	Rank
Lack of analytical skills among HR professionals	4.12	0.78	1
Data quality and integration issues	4.05	0.82	2
Resistance to data-driven culture	3.89	0.91	3
Technological infrastructure limitations	3.76	0.87	4
Privacy and ethical concerns	3.68	0.94	5
Lack of management support	3.52	0.89	6
Cost of implementation	3.41	0.96	7

Scale: five response points. Means, standard deviations, and ranks reproduced exactly from the source.

5. Discussion

5.1. Interpretation of the HRA–performance association

Conditional on confirmation of the model statistics, the positive source-reported HRA–OFP association is consistent with the proposition that better workforce information can support improved decisions on recruitment costs, retention strategies, resource allocation, and personnel budgets. This interpretation should be distinguished from a claim of financial causality. Because OFP is measured through managerial perceptions at one point in time, stronger performance may also enable organizations to invest in HRA capabilities, or both variables may reflect unmeasured managerial competence (Marler & Boudreau, 2017; Angrave et al., 2016).

5.2. The organizational function of evidence-based management

EBM provides a theoretically plausible mechanism linking analytical tools to decisions that managers can justify and implement. The reported EBM mediation suggests that the value of HRA may depend on evidence-processing routines, not only on data collection. The conceptual point aligns with research showing that analytic quality and strategic capacity to act determine whether a technical capability becomes useful in practice (Minbaeva, 2018; Mushtaq et al., 2024; Sivakumar, 2025). A stronger future test should establish temporal precedence and assess managerial decision quality separately from the performance outcome.

5.3. Why accounting integration matters

The reported AI pathway highlights a potentially distinctive contribution: financial planning processes can make workforce insights relevant to organizational budget choices. For example, turnover forecasts can be translated into anticipated recruitment and onboarding expenditure; training assessments can be linked to cost and productivity scenarios; and workforce plans can be reviewed against labor expense ratios and financial constraints. These examples illustrate possible uses of integrated analytics; they are not separately measured implementation effects in this survey. More rigorous research should test whether specific integrated planning routines improve objective financial outcomes (Ali, 2025; Mohamed & Shehata, 2023).

5.4. Competitive advantage, sector context, and implementation capability

From a resource-based perspective, any sustainable advantage is likely to rest on the difficult-to-replicate combination of high-quality data, analytical expertise, cross-functional trust, and the ability to convert insights into coordinated action, rather than on generic software adoption (Barney, 1991; Minbaeva, 2018). The stronger reported financial-services association may reflect differences in data maturity, organizational form, or respondents' perceptions; however, no explanatory industry-level variables were measured to adjudicate these possibilities. Sectoral interpretations should therefore remain hypotheses for follow-up research.

5.5. Managerial recommendations for Armenian organizations

The descriptive barrier rankings support a staged implementation agenda. First, HR and finance leaders can establish common definitions for workforce costs, turnover, staffing, and financial performance. Second, organizations can invest in analytical literacy, transparent data-quality checks, and clear rules on workforce-data access. Third, pilot applications should begin with concrete managerial decisions—such as recruitment budgeting or retention cost forecasting—with a documented decision owner and a predefined success metric. Fourth, a governance process should review fairness, proportionality, privacy, and employee impact. These recommendations follow from the study's conceptual framing and perceived obstacles; their effectiveness was not experimentally tested (Angrave et al., 2016; Tursunbayeva et al., 2018; Khaliq & Saritha, 2023; Ramzi et al., 2021).

Table 9. Proposed HR–accounting integration implementation framework (authorial synthesis)

Phase	Managerial action	Illustrative indicator
1. Data foundation	Harmonize HR and finance definitions; establish access roles and audits	Completeness and consistency of cost/employee records
2. Analytical capability	Train HR/finance staff; document model assumptions	Analytical competency and error rates
3. Decision integration	Embed HR metrics in budgets, investment cases, and variance reviews	Share of decisions with documented evidence
4. Impact evaluation	Specify baseline and time horizon; compare to objective outcomes	Verified cost, turnover and productivity change
5. Responsible governance	Assess bias, privacy, proportionality and feedback	Policy compliance and employee-appeal process

This implementation framework is an interpretive recommendation derived from the study and cited literature; it is not a ninth empirical result table.

5.6. Theoretical contributions

The study's primary theoretical contribution is to distinguish analytical adoption from its organizational translation mechanisms. HRA is conceptualized as an information-processing capability, EBM as a decision routine, and AI as a cross-functional interface linking workforce insight with financial evaluation. This distinction extends the discussion beyond generic statements that more analytics yields more performance, while preserving the original claim that coordinated use of human capital information may contribute to competitive positioning (Barney, 1991; Marler & Boudreau, 2017; Minbaeva, 2018).

5.7. Limitations and future research

The first limitation is temporal: a single-wave survey cannot support a causal sequence between HRA adoption, EBM, AI, and financial performance. Second, use of common informants and self-report measures may

introduce common-method bias; the source mentions remedies but provides neither the procedures nor corresponding diagnostic results. Common-method risk should not be represented as controlled without evidence (Podsakoff et al., 2003). Third, OFP is perceived rather than objectively audited. Fourth, information about the sampling frame, questionnaire items, subgroup measurement invariance, and exact ethical approval is incomplete. Fifth, the original model includes internal numerical inconsistencies across path coefficients, correlations, and explained variance; the full structural model should be rerun and replaced with a coherent, archived output before submission. Finally, all respondents were drawn from the Armenian setting, limiting extrapolation to other countries.

Future research should employ longitudinal or multi-source designs, integrate audited performance indicators, test sectoral contingencies with measurement invariance, and compare specific use cases such as turnover forecasting and HR investment appraisal. Replication will require de-identified data, complete item definitions, codebooks, and analysis outputs under appropriate confidentiality conditions.

6. Conclusion

This article examines the original survey evidence on the integration of HR analytics into accounting-based decision-making among 287 respondents associated with Armenian organizations. The source reports positive direct and mediated relationships among HRA adoption, evidence-based management, accounting integration, and perceived financial performance, alongside substantial skill and data-quality challenges. These patterns make a plausible case for treating HR analytics as a cross-functional managerial capability rather than solely as an HR reporting technology. However, the findings establish associations in respondents' perceptions, not verified improvements in audited financial performance or sustained competitive advantage. Before journal submission, the original PLS-SEM outputs require reconciliation against the measurement correlations and R^2 values. Subject to that essential validation, the study offers a contextual contribution to the debate on how workforce information enters financially consequential organizational decisions.

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