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Research Article

The Role of Artificial Intelligence in HRM–Marketing Integration: A PLS-SEM–Informed Review

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ABSTRACT

AI is revolutionizing HRM and marketing through data-driven decision-making, predictive analytics, and automated workflows. Academic research on AI-driven HRM–Marketing integration has grown as companies adopt AI-enabled employee and customer strategies. Partial Least Squares Structural Equation Modelling (PLS-SEM) is the leading analytical method for modelling complex, multidimensional, and often formative phenomena, including AI capability, people analytics, customer analytics, and cross-functional performance. However, a systematic evaluation of PLS-SEM in this intersection is absent. This systematic literature review synthesizes 97 peer-reviewed studies (2015–2025) from Scopus and Web of Science using PRISMA 2020. The review highlights internal–external experience alignment, cross-domain predictive analytics, and algorithmic coordination as AI-enabled integration pathways. While PLS-SEM is well-suited for capturing these relationships, findings reveal methodological inconsistencies, such as weak justification, limited algorithm configuration reporting, insufficient predictive assessment, and underuse of advanced techniques (e.g., higher-order constructs, PLSpredict, FIMIX-PLS, endogeneity controls). This paper demonstrates how AI promotes cross-functional HRM–Marketing alignment and offers best practices to improve the rigour, transparency, and predictive value of future PLS-SEM–based research.

Keywords: *Artificial Intelligence; Cross-Functional Alignment; HRM–Marketing Integration; PLS-SEM; Predictive Analytics*

1. INTRODUCTION

1.1 Background

AI is transforming organizations by reshaping data collection, analysis, and application for strategic decision-making (Jordan & Mitchell, 2020). Adoption has been particularly strong in HRM and Marketing, two previously separate domains that are now interconnected in data-driven organizations. In HRM, AI improves talent acquisition, workforce deployment, and decision accuracy by supporting predictive recruitment, performance analytics, algorithmic decision-making, and employee experience monitoring (Meijerink et al., 2021; Upadhyay & Khandelwal, 2018; Chakraborty et al., 2020). AI is shifting HRM from administrative functions to augmented intelligence, robotics, and digital workforce management (Dhawale & Derle, 2024).

Modern marketing relies on AI for personalized customer journeys, segmentation, real-time targeting, conversational interfaces, and predictive forecasting (Davenport et al., 2020; Huang & Rust, 2021; Panwar et al., 2024). AI-driven marketing solutions enhance organizations' ability to anticipate client needs, refine campaigns, and improve financial performance through data-driven insights. Increasingly, HRM and Marketing are converging in AI-enabled contexts, particularly in employer branding, customer experience management, and workforce–customer engagement (Alves Pereira & Veiga, 2025).

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Traditionally, HRM and Marketing have been linked through internal marketing, service culture, and employer branding. AI now provides a structural and analytical foundation for deeper integration. For example, Rahman et al. (2024) show that AI-driven HRM systems influence service quality by shaping talent capacities, frontline employee engagement, and behavioral consistency. Conversely, AI-driven marketing insights into customer expectations and behavior inform HRM policies on talent development, training, and resource allocation. AI thus improves each function individually while creating cross-functional synergies that were previously difficult to perceive or quantify. Grewal et al. (2023) note that organizations are moving toward integrated, analytics-driven ecosystems that optimize personnel skills and customer value creation.

As AI-related constructs—such as employee capabilities, customer experience variables, and cross-functional outcomes—are complex and interdependent, empirical researchers increasingly employ Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess their relationships. PLS-SEM enables the analysis of intricate structural models, including reflective and formative constructs, higher-order structures, mediating mechanisms, and predictive components (Hair et al., 2022). It is particularly suitable for examining emerging technologies like AI in HRM–Marketing contexts due to its adaptability for non-normal data, small-to-medium sample sizes, and exploratory research designs (Shela et al., 2023). Despite its potential, systematic research on the application of PLS-SEM to AI-driven HRM–Marketing integration remains limited, undermining methodological rigour and consistency in existing empirical work.

1.2 Conceptual Definition of AI-Driven HRM–Marketing Integration

AI-driven HRM–Marketing integration aligns employee and customer processes, strategies, and outcomes through intelligent algorithms, predictive analytics, and automated decision-support systems. This integration demonstrates how AI connects HRM and Marketing—traditionally distinct areas—to improve organizational performance via data-driven solutions.

Integration occurs through shared data architectures, unified analytic platforms, and algorithmic tools that track both employee and customer behavior. AI-enabled HRM solutions, such as talent analytics, digital recruitment, performance prediction, and AI-supported training, influence customer-facing operations by shaping staff capabilities, service behaviors, and frontline engagement. Conversely, AI-driven marketing capabilities—including customer analytics, forecasting, personalization, and real-time targeting—inform HRM decisions on capability building, workforce planning, and customer-centric skill development.

AI-driven HRM–Marketing integration can be understood across three interrelated dimensions:

1. AI-enabled HRM features

Digital recruitment, people analytics, and learning systems enhance employee readiness, behavioral consistency, and service quality.

2. AI-driven marketing tools

Customer analytics, predictive modelling, and customized engagement improve customer satisfaction, loyalty, and perceived value.

3. Cross-functional linkage mechanisms

AI connects HRM and Marketing by enabling shared insights, coordinated decision-making, and synchronized internal–external experience management.

Through these mechanisms, AI helps organizations align internal experiences (staff engagement, training, well-being) with external outcomes (customer satisfaction, loyalty, perceived service quality). By integrating employee and customer data, firms can improve agility, creativity, and value generation. Ultimately, AI-driven HRM–Marketing integration optimizes both employee and customer experiences through intelligent systems.

1.3 Rationale for Studying Integration Using PLS-SEM

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Methodologies for studying AI-driven HRM–Marketing integration must capture complex, multifaceted, and interrelated phenomena. PLS-SEM is particularly well-suited for this purpose because it accommodates formative indicators, higher-order components, latent variables with limited theoretical development, and prediction-oriented relationships (Hair et al., 2022). Many constructs in this domain—such as AI capability, people analytics maturity, customer analytics capability, experience alignment, and algorithmic coordination—cannot be meaningfully represented by single indicators. PLS-SEM enables researchers to specify constructs as reflective, formative, or hierarchical structures and to analyses their interactions within cross-functional systems.

AI-enabled integration research often involves intricate structural models, including mediation, moderation, and multi-layered causal pathways. PLS-SEM is especially effective in these contexts, as it can model higher-order constructs such as digitalization, analytics intensity, and cross-functional alignment using repeated indicators, two-stage, or hybrid approaches (Chinnaraju, 2025). Because integration studies frequently aim to predict outcomes such as organizational attractiveness, customer satisfaction, service quality, and financial growth, PLS-SEM's predictive orientation adds significant value (Panwar et al., 2024).

Another rationale is that AI-driven integration remains a developing research field with an evolving theoretical basis. PLS-SEM is a reliable tool for exploratory modelling and theory building, particularly when constructs are new, correlations unstable, and empirical evidence still emerging (Sarstedt & Liu, 2024). Its robustness with non-normal data, small-to-medium sample sizes, and complex model architectures makes it ideal for exploring AI-enabled cross-functional dynamics.

Despite these advantages, PLS-SEM has not been extensively or consistently applied in empirical studies on AI's impact across HRM and Marketing. To strengthen methodological rigour in this interdisciplinary domain, a systematic review is needed to evaluate current practices, identify shortcomings, and provide guidance for future applications.

1.4 Literature Gaps and Research Purpose

Despite the rapid growth of AI research in management domains, few studies examine how AI integrates HRM and Marketing. Most research treats AI in HRM and AI in Marketing separately, without considering how AI simultaneously influences internal employee processes and external customer outcomes (Upadhyay et al., 2021). This fragmented approach overlooks the cross-functional nature of AI-enabled organizational systems.

Second, existing studies rarely address AI-enabled cross-functional skills or employee–customer interactions. Key integration mechanisms such as experience alignment, algorithmic coordination, and cross-domain analytics remain underdeveloped, leading to weak theoretical foundations for AI-driven HRM–Marketing integration.

Third, while PLS-SEM is widely used to study AI-related phenomena, no comprehensive evaluation has assessed its compliance with recommended methodological standards. Common issues include inconsistent construct operationalization, ambiguous measurement model specification, insufficient reporting of algorithm configurations, and limited use of predictive assessment methods such as PLSpredict. Advanced techniques—including higher-order modelling, heterogeneity analysis (e.g., FIMIX-PLS), and endogeneity controls—are also rarely applied (Shela et al., 2023).

Artificial intelligence and digital transformation are essential to the future of the retail and e-commerce industries in Saudi Arabia. The Saudi Vision 2030 has made technological advancements a top goal for Saudi markets. It acts as a catalyst for digital transformation by fostering an environment conducive to innovation, succession planning, entrepreneurship, and technological adoption (Rahman, M.N 2024), New Advances in Business, Management and Economics Vol. 10

Finally, limited empirical evidence exists on how AI-driven analytics enhance internal–external experience alignment, organizational agility, and cross-functional coordination. Conceptual discussions suggest that AI could improve employee and customer experiences, but empirical investigations remain scarce.

In response to these shortcomings, this systematic literature review aims to:

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1. Summarize empirical research on AI-driven HRM–Marketing integration, identifying key themes, constructs, and integration pathways.

2. Assess methodological rigor in PLS-SEM applications within this domain, including model formulation, measurement practices, and advanced analytical techniques.

3. Provide conceptual and methodological insights to guide future research on AI-enabled cross-functional capabilities and strengthen PLS-SEM applications in HRM–Marketing integration.

2. REVIEW METHODOLOGY

To ensure transparency and reproducibility, this systematic review followed the PRISMA 2020 framework, which provides established guidelines for identifying, evaluating, and reporting research. PRISMA is widely adopted in management and social science research due to its reputation for enhancing reliability and repeatability. The review focused on empirical studies that used PLS-SEM as their primary analytical tool and investigated AI-related constructs in HRM, Marketing, or cross-functional frameworks. The following subsections detail the search strategy, eligibility criteria, quality assessment, and synthesis approach.

2.1 Search Strategy and Selection Criteria

A systematic and repeatable search strategy was designed in accordance with PRISMA 2020 to identify empirical studies employing PLS-SEM in AI-driven HRM–Marketing contexts. The search was intentionally broad, covering information systems, business management, HRM, and marketing, reflecting the cross-disciplinary nature of the topic. Scopus and Web of Science were selected for their robust indexing of peer-reviewed management research. Keywords related to artificial intelligence (AI), machine learning, algorithmic decision-making, human resource management (HRM), digital HRM, people analytics, marketing (customer experience, personalization, customer analytics), cross-functional integration (HRM–Marketing integration, employee–customer experience), and methodological terms (PLS-SEM, partial least squares, structural equation modelling) were combined using Boolean operators.

Search strings linked these topics with AND/OR operators to capture studies that addressed AI, HRM or HR analytics, marketing or customer experience, and PLS-SEM. To reflect the rapid growth of AI adoption and recent advances in PLS-SEM techniques, the review focused on publications from 2015 to 2025. Results were limited to peer-reviewed, English-language journal articles. Duplicate records were removed using a reference management system. Studies outside the scope—such as technical AI engineering papers, chemometrics applications of PLS, or articles unrelated to HRM, marketing, or SEM—were excluded at the title and abstract stage. Full-text screening was then applied to the remaining set.

2.2 Eligibility and Inclusion

Eligibility and inclusion were conducted in four stages, consistent with PRISMA 2020:

Stage 1: Identification

Search results from Scopus and Web of Science were compiled into a reference management file, and duplicates were removed.

Stage 2: Title and Abstract Screening

Studies were excluded if they:

- did not apply AI in business, HRM, marketing, or cross-functional settings

- did not include HRM, marketing, or employee–customer frameworks

- did not use structural equation models

- focused solely on technical AI development (e.g., algorithm engineering)

- lacked relevance to management, HRM, marketing, or information systems

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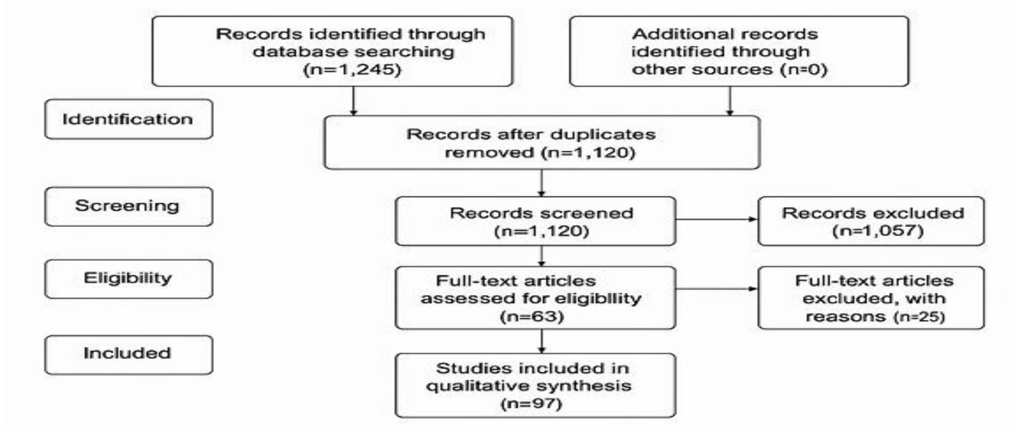

Figure 1: PRISMA 2020 flow diagram

Stage 3: Full-Text Assessment

Remaining studies were assessed against detailed inclusion criteria. To qualify, a study had to:

a. Present original empirical research using survey, field, experimental, or secondary data

b. Focus on business, management, HRM, marketing, or IT contexts

c. Use PLS-SEM (Smart PLS, Warp PLS, ADANCO, or R-based programs) as the main analytical tool

d. Address AI adoption, capabilities, people analytics, AI-enabled consumer analytics, or chatbot usage

e. Link HRM and Marketing directly or through cross-functional constructs (e.g., internal branding, employee–customer alignment, AI-enabled service excellence)

f. Be published between 2015 and 2025

g. Be available in English

Studies were excluded if they:

- discussed PLS-SEM conceptually but did not apply it empirically
- focused only on AI in marketing without HRM, or vice versa
- presented methodological PLS-SEM work unrelated to AI or HRM–Marketing integration
- reported scale development or psychometric validation without AI relevance
- were non-journal publications (e.g., theses, book chapters, editorials)

Disagreements during full-text assessment were resolved through independent review by two judges to minimize bias.

Stage 4: Final Inclusion

After applying all criteria, 97 empirical studies were selected for qualitative synthesis. These studies represent the current body of research on AI-driven HRM–Marketing integration using PLS-SEM.

2.3 Quality Assessment

To ensure methodological rigour, each study was evaluated against established best practices for PLS-SEM research in management, HRM, and marketing. The assessment covered multiple dimensions to guarantee robustness, transparency, and analytical standards.

The assessment examined the following criteria:

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1. Theoretical and Construct Quality
○ Clear conceptual framework and theoretical justification
○ Appropriate construct operationalization
○ Explicit rationale for employing PLS-SEM (e.g., prediction orientation, model complexity, formative indicators)
2. Measurement Model Evaluation
○ Accurate specification of reflective, formative, or higher-order constructs
○ Reporting of indicator reliability, internal consistency (Cronbach's alpha, composite reliability), convergent validity (AVE), and discriminant validity
○ Transparency regarding data characteristics (normality, missing values, outliers)
3. Structural Model Evaluation
○ Accurate specification of reflective, formative, or higher-order constructs
○ Reporting of indicator reliability, internal consistency (Cronbach's alpha, composite reliability), convergent validity (AVE), and discriminant validity
○ Transparency regarding data characteristics (normality, missing values, outliers)
4. Advanced PLS-SEM Techniques
○ Use of higher-order constructs (e.g., repeated indicators, two-stage, hybrid approaches)
○ Analysis of mediation and moderation effects
○ Tests for heterogeneity (e.g., FIMIX-PLS, PLS-GA, multigroup analysis)
○ Treatment of endogeneity
○ Application of significance–performance map analyses
5. Report Transparency and Completeness
○ Clear reporting of sample size and power analysis
○ Comprehensive documentation of estimation settings and analytical choices
○ Consistency between theoretical justification, measurement specification, and structural modelling

Studies that demonstrated thorough methodological reporting and adherence to PLS-SEM guidelines were classified as higher quality. Articles with major methodological shortcomings—such as poor construct specification, missing reliability/validity tests, or incomplete structural model reporting—were retained for descriptive purposes but not considered exemplars of best practice. This quality assessment strengthens the credibility of the review's conclusions and provides a foundation for methodological recommendations in future research.

2.4 Qualitative Synthesis

After finalizing the eligible studies, a qualitative synthesis was conducted to integrate conceptual insights and methodological aspects of AI-driven HRM–Marketing integration research using PLS-SEM. Data were extracted across multiple dimensions, including:

- AI capabilities, people analytics, consumer analytics, and algorithmic tools
- HRM and marketing variables
- Theoretical foundations of the models
- Structural features such as mediation, moderation, and hierarchical constructs
- Measurement and structural model characteristics
- Key empirical findings and integration mechanisms s

The synthesis was complemented by a descriptive analysis of publishing trends, journal distribution (HRM, marketing, information systems, cross-disciplinary outlets), and authorship patterns by region. Each PLS-SEM model was coded against six methodological criteria adapted from strategic management and marketing reviews:

1. Rationale for using PLS-SEM (prediction orientation, model complexity, formative constructs)
2. Data characteristics (sample size, strategy, normality, missing values, outliers)
3.Model features (number of constructs/indicators, measurement model types, higher-order constructs)
4. Measurement and structural evaluation methods
5. Advanced techniques (mediation, moderation, heterogeneity analysis, nonlinear effects, endogeneity handling)

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6. Reporting practices software used, algorithm parameters, estimation transparency)

This coding revealed methodological tendencies, best practices, and areas requiring improvement.

The thematic synthesis identified three dominant pathways through which AI supports HRM–Marketing integration:

1. Internal–External Experience Alignment

AI enhances the alignment between employee experience (engagement, capability, well-being) and customer experience (satisfaction, loyalty, perceived service quality), creating a unified internal–external value chain.

2. Cross-Domain Predictive Analytics

AI-enabled analytics generate insights that simultaneously inform HRM and Marketing decisions, linking people-related and customer-related outcomes through shared predictive intelligence.

3. Algorithmic Coordination Mechanisms

AI systems facilitate real-time coordination between employee behaviors and customer interactions, strengthening cross-functional responsiveness and service consistency.

Together, these pathways provide a framework for understanding how AI-driven systems connect internal processes with external market outcomes, and how PLS-SEM models can capture these interactions. The synthesis underpins the methodological and theoretical recommendations presented in subsequent sections.

3. FINDINGS AND DISCUSSION

This section explains what the qualitative synthesis results mean by linking them to theory frameworks, methodological practices, and real-world uses. On 97 peer-reviewed studies released between 2015 and 2025, it is based.

3.1 Conceptual Insights

According to the review, AI makes HRM-Marketing integration easier in three ways:

Internal–External Experience Alignment: By facilitating real-time feedback, predictive workforce planning, and individualized service delivery, AI improves the relationship between staff engagement and customer happiness.

Cross-Domain Predictive Analytics: By combining workforce and customer analytics, businesses may predict market trends and talent requirements at the same time, establishing a feedback loop between marketing and human resource management.

Algorithmic Coordination: AI-driven technologies, such as chatbots and recommendation engines, improve cross-functional cooperation and decision accuracy, guaranteeing operational synergy and service uniformity.

These techniques collectively demonstrate how AI unifies marketing and human resource management from separate departments into a single, data-driven framework for organizational effectiveness.

Pathway	Key Constructs	Mechanisms
Internal–External Experience Alignment	Employee engagement, capability, well-being; Customer satisfaction, loyalty, service quality	Real-time feedback loops, predictive workforce planning, personalized service delivery
Cross-Domain Predictive Analytics	Workforce analytics, customer data, employee competencies, marketing performance outcomes	Integrated predictive modelling, talent forecasting, customer trend analysis
Algorithmic Coordination Mechanisms	Decision accuracy, process efficiency, cross-functional collaboration	AI-driven automation, recommendation systems, algorithmic scheduling, process standardization

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Table 1. Pathways of AI-Enabled HRM–Marketing Integration

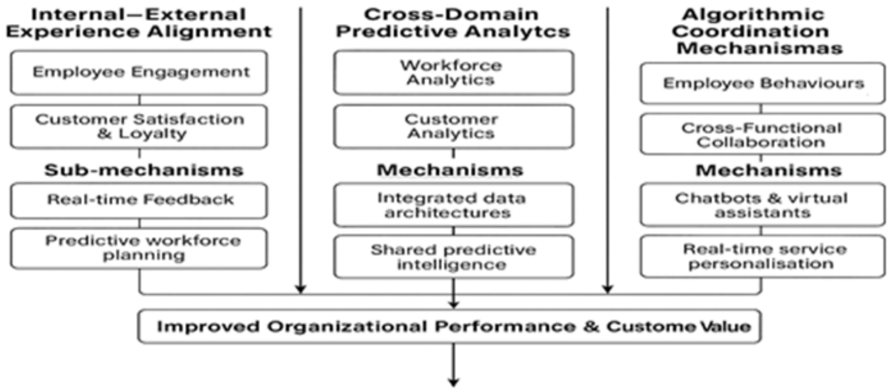

Figure 2 – Strategic Framework for Integrated Experience and Analytics

3.2 Methodological Evaluation

PLS-SEM was the most popular technique for modelling intricate interactions between latent factors across the 97 investigations.

Strengths: Increasing transparency in bootstrapping and reporting tools, adopting higher-order notions, and thoroughly testing mediation/moderation effects.

Weaknesses: Limited reporting of discriminant validity (HTMT), inconsistent construct specification (reflective vs. formative), underutilization of predictive techniques such as PLSpredict, and inadequate endogeneity controls.

Gaps: The predictive power of PLS-SEM was not completely utilized in many experiments, and methodological rigour varied greatly, making results less comparable.

Dimension	Trends	Strengths	Gaps/Weaknesses
Usage of PLS-SEM	Widely applied for complex latent constructs and predictive analysis	Robust testing of mediation/moderation; multi-level models	Limited exploitation of predictive capabilities (PLSpredict)
Construct Specification	Increasing use of higher-order constructs	Clear rationale in some studies	Inconsistent distinction between reflective vs. formative indicators
Measurement Practices	Reporting of reliability and convergent validity common	Composite reliability and AVE often reported	Discriminant validity (HTMT) underreported; incomplete diagnostics
Advanced Techniques	Rarely applied	Some mediation/moderation analysis	Limited heterogeneity analysis (FIMIX-PLS, PLS-GA), endogeneity controls, nonlinear modelling

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Reporting Transparency	Software (SmartPLS, WarpPLS, ADANCO) increasingly documented	Bootstrapping configurations sometimes reported	Insufficient documentation of algorithm parameters, subsample counts, estimation settings
Sample Size	Small-to-medium samples typical	Some justification provided	Inadequate power analysis in many studies

Table 2. Methodological Trends, Strengths, and Gaps in PLS-SEM Studies

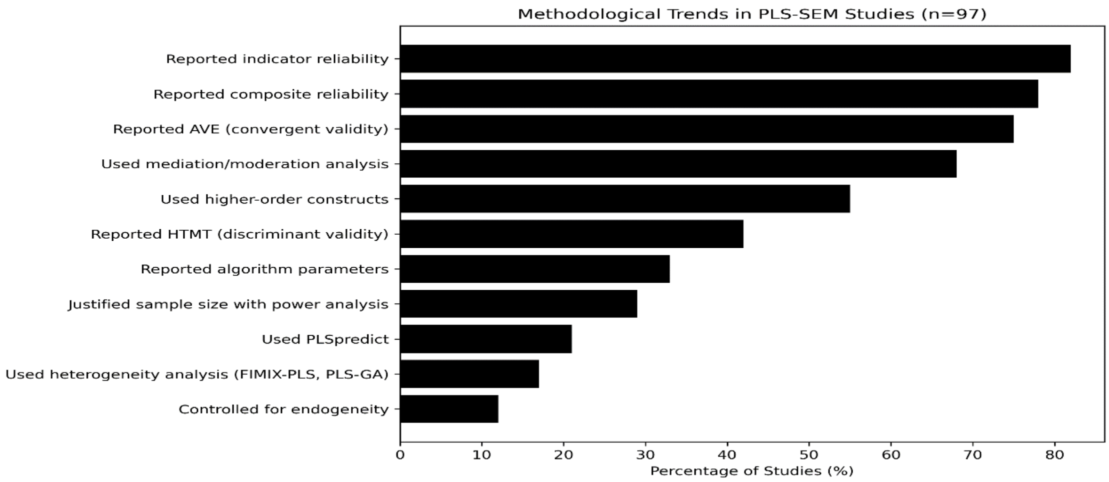

Figure 3 – Methodological Trends in PLS-SEM Studies (n=97)

3.3 Implications for Research and Practice

For Research: Strict PLS-SEM procedures, such as endogeneity testing, heterogeneity analysis, and predictive assessment (PLSpredict), should be used in future investigations. Longitudinal and cross-industry designs are required to improve generalizability.

For Practice: Businesses can use AI for algorithmic decision support, predictive planning, and workforce-customer alignment. Businesses can measure integration results by using strong PLS-SEM insights, which promotes agility and strategy coherence.

Overall Contribution: This analysis shows that integrating AI-driven HRM and marketing is both a theoretical challenge and a practical requirement. Enhancing PLS-SEM's methodological rigor will boost academic credibility and give businesses useful foundations for utilizing AI.

4. CONCLUSION

This systematic review shows that AI-driven HRM–Marketing integration transforms how businesses connect internal worker capabilities with external customer experience. The review of 97 peer-reviewed studies from 2015 to 2025 found three main pathways—internal–external experience alignment, cross-domain predictive analytics, and algorithmic coordination mechanisms—that explain how AI improves cross-functional coherence and organizational performance. AI unites employee- and customer-facing tasks through real-time feedback loops, predictive workforce planning, personalized customer experiences, shared predictive intelligence, and automated decision-support tools.

The review shows that PLS-SEM is the most used analytical method for modelling complicated, multidimensional connections. Its versatility makes it ideal for emerging AI constructs like higher-order structures, formative indicators, and prediction-oriented models. However, inconsistent construct specification, limited discriminant validity reporting, insufficient PLS-SEM justification, and underuse of advanced analytical techniques like

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heterogeneity testing, endogeneity controls, and PLSpredict persist across the literature. These methodological weaknesses must be addressed to improve future study rigour, transparency, and prediction power.

The review makes two key contributions. It presents a complete paradigm for how AI-driven technologies merge HRM and Marketing to improve experience management, service quality, and strategic agility. It suggests stronger construct reasoning, more complete reporting, and greater adoption of advanced modelling processes to improve PLS-SEM applications in this sector.

In conclusion, AI-driven HRM–Marketing integration is a strategic requirement for companies and organizations seeking competitive advantage through linked employee–customer value generation. Future research should use more rigorous analytical criteria, cross-industry and longitudinal designs, and examine how intelligent systems change internal–external experience management. This research will improve theoretical development and give organizations' greater evidence-based foundations for using AI to maximize workforce and customer results.

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