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AI-DRIVEN SPORTS MARKETING AND FAN OUTCOMES IN PROFESSIONAL SPORTS LEAGUES

A Theory-Driven Empirical Research Manuscript

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ABSTRACT

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Artificial intelligence is now woven into professional sports marketing, showing up in personalized content, recommendation engines, automated fan communication, predictive analytics, and data-driven fan services. Even so, solid empirical evidence on how AI-enabled personalization actually shapes fan engagement and downstream commercial outcomes is still thin, especially in South Asian professional sport. This paper sets out a theory-driven model connecting perceived AI-driven personalization to fan engagement, brand loyalty, and purchase intention.

The model draws on UTAUT2, on Yoshida et al.'s (2014) sport-fan engagement framework, and on Puntoni et al.'s (2021) consumer–AI experiential perspective, treating fan engagement as the mediating mechanism and team identification and perceived algorithmic depersonalization as boundary conditions. The proposed design is a cross-sectional survey of adult professional-sport fans who have used at least one AI-enabled fan touchpoint, with Partial Least Squares Structural Equation Modeling (PLS-SEM) as the intended analytical approach — covering measurement-model assessment, structural path estimation, bootstrapped mediation and moderation tests, conditional indirect effects, predictive assessment, and robustness checks.

What follows is the theoretical model, hypotheses, measurement framework, survey instrument, and a fully pre-specified statistical protocol. No respondent-level dataset has yet been collected for this manuscript, so no numerical results are reported here; the protocol is written so that genuine survey data can be dropped in and analyzed later without needing to invent coefficients, significance levels, reliability estimates, or fit statistics.

KEYWORDS*: Artificial Intelligence; Sports Marketing; Fan Engagement; Brand Loyalty; Purchase Intention; Personalization; Team Identification; Algorithmic Depersonalization; PLS-SEM*
JEL Codes: M31, L83, O33

1. INTRODUCTION

1.1 Background and Research Context

Professional sports organizations now function, in many respects, as data-intensive entertainment businesses. Ticketing platforms, streaming services, mobile apps, social media, customer databases, and digital commerce all generate behavioral data that can be mined to personalize communication and commercial offers. AI turns this data into individualized recommendations, automated fan-service interactions, predictive targeting, and real-time content delivery. Sport-management scholars have also begun paying closer attention to what might be called algorithmic fandom — the opportunities AI creates for fan relationships, alongside the risks it introduces.

Personalization is not something to treat as automatically beneficial, though. When an algorithm gets a fan's interests right, the interaction can feel relevant and even validating. When it misses — recommendations that are off-target or feel intrusive — fans may instead experience what researchers call algorithmic depersonalization: a sense of distrust, or a feeling that the brand doesn't really see them as individuals. This tension matters more in sport than in most consumer categories, because fandom isn't just about consumption utility; it is bound up with identity, community, ritual, emotional attachment, and loyalty to a team.

1.2 Problem Statement

Sport organizations are pouring resources into AI-enabled marketing on the assumption that personalization will deepen fan engagement and, eventually, loyalty and spending. The sport-AI literature backing that assumption, however, remains fragmented — leaning heavily on conceptual discussion, expert interviews, and case studies rather than hypothesis-tested quantitative evidence. What is missing is a model that actually tests the mechanism by which AI personalization might influence fan outcomes, and that identifies the conditions under which the relationship strengthens or weakens.

1.3 Research Gap

- Theoretical gap: Technology-adoption theory and sport-specific fan-engagement theory are rarely combined into a single, empirically testable AI-marketing model.
- Empirical gap: Quantitative, hypothesis-tested evidence linking AI personalization to fan engagement and commercial outcomes is still limited.
- Contextual gap: Most empirical work on AI personalization sits outside sport altogether, even though sport fandom carries identity and community dynamics that could change how consumers respond.
- Mediating-mechanism gap: Fan engagement has not been adequately tested as the mechanism linking AI personalization to loyalty and purchase intention.
- Boundary-condition gap: Team identification and perceived algorithmic depersonalization could plausibly change the strength of the personalization–engagement link, but sport-AI research has given them little quantitative attention.
- Geographical gap: South Asian professional sport — including India's major leagues — remains underrepresented in theory-driven, quantitative research on AI-enabled fan marketing.

1.4 Research Objectives

RO1: To examine the effect of perceived AI-driven personalization on sport-fan engagement.
RO2: To examine the effects of fan engagement on brand loyalty and purchase intention.
RO3: To test the mediating role of fan engagement in the relationships between AI-driven personalization and brand loyalty and purchase intention.
RO4: To examine whether team identification moderates the relationship between AI-driven personalization and fan engagement.
RO5: To examine whether perceived algorithmic depersonalization weakens the relationship between AI-driven personalization and fan engagement.
RO6: To generate context-specific evidence from professional sport in South Asia to inform AI-enabled sport-marketing practice and policy.

1.5 Research Questions

RQ1: Does perceived AI-driven personalization significantly predict fan engagement?
RQ2: Does fan engagement significantly predict brand loyalty and purchase intention?
RQ3: Does fan engagement mediate the relationships between AI-driven personalization and brand loyalty and purchase intention?
RQ4: Does team identification strengthen the relationship between AI-driven personalization and fan engagement?
RQ5: Does perceived algorithmic depersonalization weaken the relationship between AI-driven personalization and fan engagement?
RQ6: What implications do the findings have for AI deployment and responsible sport-marketing practice in South Asian professional leagues?

2. THEORETICAL FOUNDATION AND CONCEPTUAL MODEL

2.1 UTAUT2

UTAUT2 supplies the technology-adoption logic behind how consumers respond to AI-enabled touchpoints. Its consumer-facing extension folds in performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit. Applied here, the theory explains why fans might respond well to AI-driven personalization when the technology feels useful, easy to use, and genuinely enjoyable to interact with.

2.2 Sport-Fan Engagement

Yoshida et al. (2014) defined fan engagement as a sport-specific behavioral construct built from management cooperation, prosocial behavior, and performance tolerance. That framing is useful here because it separates active fan behavior from simple team identification or one-off transactional consumption. This study accordingly treats fan engagement as the central mechanism through which AI-enabled personalization might shape loyalty and purchase-related outcomes.

2.3 Consumer–AI Experiential Perspective

Puntoni et al. (2021) argue that consumer–AI interactions carry both upside and downside: AI can sharpen relevance and convenience, but a misclassified recommendation can just as easily create a negative experience. This study captures that downside through perceived algorithmic depersonalization, treated as a negative boundary condition on the model.

2.4 Conceptual Model

The model treats perceived AI-driven personalization as the main antecedent of fan engagement. Fan engagement, in turn, is expected to shape brand loyalty and purchase intention, with brand loyalty also feeding forward into purchase intention. Team identification is modeled as a positive moderator of the personalization–engagement link, and perceived algorithmic depersonalization as a negative one.

3. HYPOTHESES DEVELOPMENT

H1. Perceived AI-driven personalization has a positive effect on fan engagement.
H2. Fan engagement has a positive effect on brand loyalty.
H3. Fan engagement has a positive effect on purchase intention.
H4. Brand loyalty has a positive effect on purchase intention.
H5a. Fan engagement mediates the relationship between AI-driven personalization and brand loyalty.
H5b. Fan engagement mediates the relationship between AI-driven personalization and purchase intention.
H6. Team identification positively moderates the relationship between AI-driven personalization and fan engagement.
H7. Perceived algorithmic depersonalization negatively moderates the relationship between AI-driven personalization and fan engagement.

H8. Team identification moderates the indirect effect of AI-driven personalization on purchase intention through fan engagement.

4. LITERATURE REVIEW

4.1 AI in Sport Marketing and Fan Experience

Recent literature points to personalization, predictive analytics, automated content generation, and data-driven decision-making as the AI applications that matter most in sport marketing. Done well, these can sharpen the relevance and timing of fan communication while supporting commercial goals. The same literature, though, raises real concerns about privacy, fairness, inappropriate targeting, and algorithmic filtering.

4.2 AI Personalization, Engagement, and Loyalty

Outside sport, AI personalization has repeatedly been linked to stronger consumer engagement, satisfaction, loyalty, and purchase-related outcomes. But the evidence also shows personalization can backfire when the algorithm's classification does not match what the consumer actually wants. Together, these findings support a dual-path view: AI personalization creates value when it feels relevant, but can erode relational quality when it feels inaccurate or depersonalizing.

4.3 Fan Engagement as a Mediating Mechanism

Fan engagement is treated here as a behavioral mechanism rather than simply an outcome, because sport consumers express engagement through feedback, community participation, support for fellow fans, and tolerance during a losing streak. That makes engagement a plausible bridge between AI-enabled communication and the loyalty and purchase intentions that follow.

4.4 Team Identification as a Boundary Condition

Fans who identify strongly with a team may process team-related personalization differently than those who identify weakly. Because the team is part of a highly identified fan's self-concept, relevant personalized communication can reinforce that identity and deepen engagement further. Team identification is therefore expected to strengthen the positive personalization–engagement relationship.

4.5 Algorithmic Depersonalization as a Boundary Condition

Algorithmic errors can leave fans feeling like the system does not know them as individuals. That kind of experience can erode trust and dampen the positive effect personalization would otherwise have. Depersonalization is modeled here as something that dampens the relationship, not as a standalone negative predictor in its own right.

5. METHODOLOGY

5.1 Research Design

The study takes a positivist, deductive, quantitative approach. A cross-sectional online survey is specified for the initial hypothesis test. Because cross-sectional data cannot support strong causal claims, structural-path results should be read as associational rather than causal. A follow-up two-wave design is recommended as a future robustness check.

5.2 Population and Sampling

The target population is adults aged 18 and over who follow at least one professional sports league and have used an AI-enabled fan touchpoint — a team or league app, a personalized notification, a chatbot, a recommendation feed, or AI-generated content — within the past six months. The main contextual focus is professional sport in India, with particular relevance to leagues such as the Indian Premier League, Indian Super League, and Pro Kabaddi League.

Sampling will be purposive and quota-based, monitored across age groups and league categories so the sample does not skew toward a single fan segment. Because it is a non-probability design, any population-level generalization should be made cautiously.

5.3 Sample Size and Statistical Power

The original protocol targets roughly 400 respondents, enough to support PLS-SEM along with mediation, moderation, conditional indirect-effect, and robustness analyses. Final sample adequacy should be confirmed against the actual number of usable responses and an a priori power analysis based on the finished model's complexity and the smallest effect size worth detecting. The completed paper should report the exact sample-size calculation and its assumptions rather than leaning on the 10-times rule alone.

5.4 Measurement

All focal constructs use multi-item, seven-point Likert-type indicators. AI-driven personalization captures perceived relevance, tailoring, adaptation, and timing of team/league communications. Fan engagement captures feedback behavior, prosocial support, performance tolerance, and participation. Team identification, algorithmic depersonalization, brand loyalty, and purchase intention are each measured with multi-item indicators adapted from the cited literature for a professional-sport context.

5.5 Data Screening and Quality Control

- Screen respondents for age, professional-sport fandom, and recent exposure to an AI-enabled fan touchpoint.
- Drop cases that fail attention checks or show clearly invalid response patterns.
- Check item-level missingness and document how it was handled before estimating the model.
- Inspect univariate distributions and flag multivariate outliers using Mahalanobis distance where appropriate.
- Check common-method risk through procedural remedies and statistical diagnostics such as full-collinearity VIF.
- Compare early versus late respondents as a non-response-bias check where response timestamps are available.

6. ADVANCED STATISTICAL ANALYSIS STRATEGY

The primary inferential method is Partial Least Squares Structural Equation Modeling (PLS-SEM), run in SmartPLS 4 or an equivalent validated statistical package. Analysis should follow the sequence below, with every decision documented and reported transparently.

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1. Descriptive analysis: report frequency distributions, means, standard deviations, skewness, kurtosis, and inter-construct correlations.
2. Measurement model: assess indicator loadings, Cronbach's alpha, composite reliability, rho_A, and average variance extracted (AVE).
3. Convergent validity: retain indicators based on loading and construct-level evidence, documenting any theoretically justified item removal.
4. Discriminant validity: assess HTMT and, as a supplementary diagnostic, the Fornell–Larcker criterion.
5. Collinearity: inspect VIF before interpreting structural paths and interaction terms.
6. Structural model: estimate standardized path coefficients, bootstrap standard errors, t statistics, p values, and confidence intervals using at least 5,000 bootstrap resamples.
7. Explained variance and effect size: report R^2 and f^2 for endogenous constructs, and discuss substantive rather than only statistical significance.
8. Predictive assessment: report Q^2 or the appropriate out-of-sample predictive metric available in the chosen PLS-SEM implementation.
9. Mediation: test indirect effects using bootstrap confidence intervals, distinguishing indirect-only, complementary, competitive, and no-mediation patterns from the direct and indirect effects jointly.
10. Moderation: mean-center or otherwise standardize continuous predictors before building interaction terms, estimate simple slopes, and probe conditional effects at substantively meaningful moderator levels.
11. Moderated mediation: estimate conditional indirect effects and the index of moderated mediation, with bootstrap confidence intervals.
12. Robustness: run multi-group analysis only after establishing measurement invariance across comparison groups, considering league type and age cohort where sample size permits.
13. Common-method and endogeneity sensitivity: report procedural remedies and, where justified and data permit, additional collinearity or endogeneity diagnostics rather than relying solely on Harman's single-factor test.
14. Reporting: report confidence intervals, exact p values where available, effect sizes, predictive metrics, and model decision rules — and avoid treating statistical significance as proof of causality.

Construct	Items	Loading range	Cronbach's α	Composite reliability	AVE
AI-Driven Personalization	TBD	TBD	TBD	TBD	TBD
Fan Engagement	TBD	TBD	TBD	TBD	TBD
Team Identification	TBD	TBD	TBD	TBD	TBD
Algorithmic Depersonalization	TBD	TBD	TBD	TBD	TBD
Brand Loyalty	TBD	TBD	TBD	TBD	TBD
Purchase Intention	TBD	TBD	TBD	TBD	TBD

Hypothesis	Structural / Indirect Path	β	t	p	95% CI	Decision
H1	AI Personalization → Fan Engagement	TBD	TBD	TBD	TBD	TBD
H2	Fan Engagement → Brand Loyalty	TBD	TBD	TBD	TBD	TBD
H3	Fan Engagement → Purchase Intention	TBD	TBD	TBD	TBD	TBD
H4	Brand Loyalty → Purchase Intention	TBD	TBD	TBD	TBD	TBD
H5a	AI Personalization → Fan Engagement → Brand Loyalty	TBD	TBD	TBD	TBD	TBD
H5b	AI Personalization → Fan Engagement → Purchase Intention	TBD	TBD	TBD	TBD	TBD
H6	AI Personalization × Team Identification → Fan Engagement	TBD	TBD	TBD	TBD	TBD
H7	AI Personalization × Depersonalization → Fan Engagement	TBD	TBD	TBD	TBD	TBD
H8	Conditional indirect effect on Purchase Intention	TBD	TBD	TBD	TBD	TBD

All values in the tables above are placeholders (“TBD”) pending analysis of a genuine respondent-level dataset. Section 7 explains how these tables should be completed.

7. RESULTS (PENDING DATA COLLECTION)

No respondent-level dataset has been collected for this manuscript at the time of writing, so this section intentionally does not report descriptive statistics, measurement-model estimates, structural-model estimates, mediation results, moderation results, or model-fit indices. Populating the subsections below with real numbers, drawn from an actual analysis run, is the single most important remaining step before this manuscript is ready for submission.

Once genuine survey data have been collected, this section should be completed in the following order, matching the protocol set out in Section 6:

7.1 Data Screening and Sample

Report the final usable sample size, the number and criteria for any exclusions, and confirmation that item-level missingness was handled as documented in Section 5.5.

7.2 Descriptive Statistics

Report means, standard deviations, and ranges for each construct, computed from the actual indicator scores collected.

7.3 Measurement Model Assessment

Report indicator loadings, Cronbach's alpha, composite reliability, rho_A, and AVE for each construct, generated directly by the PLS-SEM software rather than estimated by hand or approximated from a principal-component analysis.

7.4 Discriminant Validity

Report HTMT ratios — and, as a secondary check, the Fornell–Larcker criterion — for every construct pair.

7.5 Structural Model

Report standardized path coefficients, bootstrapped standard errors, t-statistics, p-values, and 95% confidence intervals for each hypothesized path, using at least 5,000 bootstrap resamples, consistent with Section 6.

7.6 Explained Variance and Effect Sizes

Report R^2 and f^2 for each endogenous construct in the model.

7.7 Mediation Analysis

Report bootstrapped indirect effects and confidence intervals for H5a and H5b, and classify the resulting mediation pattern — indirect-only, complementary, competitive, or no mediation — based on the direct and indirect effects considered together.

7.8 Moderated Mediation

Report the index of moderated mediation for H8, together with its bootstrap confidence interval.

7.9 Multicollinearity and Robustness Diagnostics

Report VIF values for all predictors and interaction terms, along with any further robustness checks — such as measurement invariance and multi-group comparisons — that the achieved sample size supports.

No coefficient, significance level, reliability estimate, or fit statistic should be entered into this section unless it is produced directly from analysis of a genuinely collected dataset. The measurement-model and hypothesis-tracking table templates in Section 6 can be reused here once real estimates are available.

8. DISCUSSION

Because no empirical data have yet been analyzed, this section outlines how the results should be interpreted once Section 7 is completed, rather than discussing specific findings.

If the data support H1 through H4, that would point to a coherent central mechanism: perceived AI-driven personalization associated with fan engagement, and fan engagement in turn associated with both brand loyalty and purchase intention. Bootstrapped indirect effects for H5a and H5b, if their confidence intervals exclude zero, would indicate that engagement functions as a meaningful pathway connecting personalization to these downstream outcomes. Whether the direct paths from personalization to loyalty and purchase intention remain significant once engagement is included in the model would indicate whether the mediation is full (indirect-only) or partial.

The moderation hypotheses (H6, H7, H8) call for particular caution in interpretation. A significant main effect for team identification or algorithmic depersonalization would not, on its own, confirm the corresponding moderation hypothesis — the interaction terms themselves need to reach significance for H6, H7, and H8 to be supported. Researchers should resist reading a strong main effect as evidence for a moderation hypothesis that the interaction term does not independently support.

Any conclusions drawn from this design should stop short of causal claims, since the proposed design is cross-sectional. If the target journal specifically requires latent-variable PLS-SEM output, the final analysis should be run in SmartPLS or an equivalent validated SEM package rather than through composite-score regression, and the reported measurement and structural estimates should match that software's output exactly.

9. THEORETICAL AND MANAGERIAL IMPLICATIONS

9.1 Theoretical Implications

If empirically supported, this model would connect consumer technology-adoption logic with a sport-specific, behavioral conception of fan engagement, and with a consumer–AI perspective that explicitly weighs both benefits and costs. That combination would extend sport-marketing research beyond the question of whether AI personalization matters, toward the more useful question of which engagement mechanism carries the effect, and under what relational conditions.

9.2 Managerial Implications

For sport marketers, the framework suggests AI investment should not be judged solely on click-through or conversion metrics. Personalization should be built around relevance, timing, transparency, and accuracy. Fan segmentation should account for team identification, and systems should build in ways for fans to correct their preferences and get transparent feedback when a recommendation misses.

9.3 Policy and Responsible AI Implications

AI-enabled fan marketing needs to be paired with real data governance — transparency, privacy safeguards, fairness monitoring, and mechanisms that let fans understand or correct how they are being personalized to. Once collected, the empirical findings from this study could inform league-level guidance on responsible use of fan data and algorithmic decision-making.

10. LIMITATIONS

The design carries several limitations worth naming upfront. A cross-sectional survey limits causal inference. Non-probability sampling can introduce selection bias. Self-reported measures are vulnerable to common-method variance. And because eligibility requires recent interaction with an AI-enabled touchpoint, digitally active fans are likely overrepresented relative to the broader fan base. How far the findings generalize will also depend on the composition of the achieved sample and how many leagues end up represented in it.

11. CONCLUSION

AI-enabled personalization is becoming a standard part of professional sports marketing, but how much commercial value it actually creates depends on how fans experience and respond to algorithmic interactions. This manuscript lays out a testable model in which AI-driven personalization shapes fan engagement, which in turn connects to brand loyalty and purchase intention, with team identification and algorithmic depersonalization specified as boundary conditions. The PLS-SEM protocol described here is built to test direct, indirect, moderated, and conditional indirect effects. The essential next step is collecting and analyzing genuine respondent-level data — no numerical findings should be added to this manuscript until that dataset exists and has actually been analyzed.

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