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Organizational Adoption Priorities for Multi-Sided Fandom Platforms: Evidence from South Korean Entertainment Firms

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Abstract

Fandom platforms connect artists, entertainment companies, and fandoms, yet evidence on firm-level adoption priorities remains limited. This study examines company experts' assessments of twelve adoption drivers and twelve inhibitors specified before data collection using the Stochastic Fuzzy Analytic Hierarchy Process (SF-AHP) with 28 respondents from eight South Korean entertainment firms. Respondents provided crisp Saaty-scale judgments, with fuzzy ranges imposed analytically and propagated through consistency-conditioned simulation. Robustness was assessed through crisp AHP, alternative aggregation and fuzzification specifications, and panel-composition checks. Artist-related conditions received the highest component priority among both drivers and inhibitors and remained first across the evaluated robustness specifications. Convenient communication tools for artists (D3) and stable monetization (D1) formed the leading driver tier, while artist fatigue (H1), excessive payment inducements (H9), and artist privacy risks (H4) formed the leading inhibitor tier, with rank variation among close alternatives. Secondary PEST summaries were classification- and aggregation-sensitive and are interpreted descriptively. The findings indicate a robust stakeholder-level coordination focus together with a concentrated set of leading factor-level priorities. These results identify a company-side priority structure for the evaluated factor set, broad adoption frame, and South Korean entertainment setting, while leaving artist- and fandom-side preferences and population-level generality for direct future study.

Keywords: fandom platforms; multi-sided platforms; organizational adoption; platform governance; dual-factor theory; stochastic fuzzy AHP; expert elicitation; creator economy

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1. Introduction

Multi-sided platforms have become one of the defining organizational forms of the digital economy. They create value by enabling interactions among two or more distinct but interdependent groups of participants and by governing, without fully controlling, those interactions [1,2]. A distinct and fast-growing segment of this landscape has formed around creators and the communities that gather around them. Fandom platforms are a vivid case in point: multi-sided environments that mediate interaction among artists, entertainment companies, and fandoms, and through which content, communication, and commerce are organized. These sides are complementary, but complementarity does not imply that they contribute equally or face symmetric incentives [3–7].

The most fully developed instance of this platform type has emerged in the Korean entertainment industry, particularly around K-pop. Against the backdrop of a global recorded-music market worth roughly USD 21.6 billion in 2020—and a South Korean market growing far faster, by 44.8% year on year, led by BTS [8]—Korean entertainment companies built dedicated platforms to intermediate artist–fan interaction at global scale, beginning with HYBE's Weverse in 2019 and SM Entertainment's Bubble in 2020. K-pop makes these platform dynamics especially visible, while participating firms also include companies managing singers and actors. The study therefore treats South Korean fandom platforms as a distinctive empirical setting in which company-mediated artist–fan coordination can be examined at scale. Table 1 compares the two leading platforms.

Table 1. Comparison of fandom platforms: Weverse and Bubble.

Category	Weverse	Bubble
Company	WEVERSE COMPANY Inc. (Seongnam, Republic of Korea; subsidiary of HYBE)	Dear U Co., Ltd. (Seoul, Republic of Korea; subsidiary of SM Entertainment)
Release date	June 2019	February 2020
Revenue (FY2025) *	299.7 billion KRW (208.2 million USD)	83.8 billion KRW (58.2 million USD)
Revenue model	Sells original content, albums, MD, concert tickets, membership subscriptions, etc.	Membership subscription
Featured Artists	• HYBE: BTS, SEVENTEEN, LE SSERAFIM • YG Entertainment: BLACKPINK, BABYMONSTER • Cube Entertainment: (G)I-DLE	• SM Entertainment: Red Velvet, NCT, Girls' Generation, aespa • JYP Entertainment: 2PM, TWICE, ITZY, Stray Kids • Starship Entertainment: Monsta X, WJSN, IVE • Actors and sports stars

* Source: Company-level figures were obtained from the FY2025 annual reports filed by the respective companies with the Republic of Korea's Data Analysis, Retrieval and Transfer System (DART). Monetary amounts originally reported in Korean won were converted into U.S. dollars using the year-end 2025 KRW/USD exchange rate published by the Bank of Korea. All source materials were accessed on 22 June 2026. Both companies use calendar-year fiscal years ending 31 December; FY2025 therefore refers to aligned annual reporting periods.

A structural tension runs through these platforms, and it motivates our inquiry. Their appeal rests on relational and social value—direct contact, community participation, and access to artist-related information and content—while their commercial viability depends on economic value generated through subscriptions, merchandise, data-enabled services, and other monetization mechanisms. They also generate informational value through exclusive content, translation, and integrated updates. These forms of value are co-created by artists, entertainment companies, and fandoms, but value creation must be distinguished from value capture [9–12]. Viable capture supports investment and continued operation; tension arises when allocation, control, workload, payment pressure, privacy risks, or weak capabilities undermine continued participation [13–15]. We therefore examine the conditions that experts perceive as encouraging or constraining a company-level adoption decision. These priorities relate to value creation insofar as they identify conditions that company experts expect to enable or constrain the participation and coordination through which value may be created, but they remain distinct from realized value creation because the study does not observe participant outcomes, value flows, or appropriation directly.

Research has already explained important parts of this setting. Prior studies examine Weverse and Bubble as business models and platform cases [16–19], communication consumption, fandom reorganization, user experience, and service improvement [20–23], and

artist labor, platform support, and the corporate mediation of fan communities [19,24–26]. These studies establish that communication, monetization, support, privacy, workload, and community design matter. They do not, however, provide a common organization-level comparison of how artist-, company-, and fandom-related adoption considerations are prioritized within separate positive and negative factor sets. The evidence limitation is therefore decision-specific, not a general absence of platform data: behavioral traces can be abundant, whereas comparable public evidence on firm-level adoption judgments, contracts, investment choices, and cross-side operating trade-offs remains limited or proprietary.

Accordingly, this study focuses on an entertainment company's organizational decision concerning whether and how to adopt a fandom-platform arrangement in light of anticipated implementation and operating consequences for artists, the company, and fandoms. Because the survey did not present proprietary platform development, participation in an existing third-party platform, and continued platform operation as separate decision scenarios, the term adoption is used here as a broad decision frame, and no mode-specific estimate is intended. The study addresses two primary research questions. (RQ1) Within the specified sets of drivers and inhibitors, which factors receive the highest priority when company-side industry experts evaluate fandom-platform adoption? (RQ2) How are these priorities distributed across artist-, entertainment-company-, and fandom-related condition blocks, and does one block receive consistently higher priority in the expert panel's judgments? As a secondary exploratory analysis, we ask how the same estimated priorities distribute across PEST categories under cumulative and category-size-adjusted summaries (EQ1 for drivers and EQ2 for inhibitors).

To address these questions, we treat fandom platforms as multi-sided ecosystems and analyze them using SF-AHP. Respondents supplied crisp pairwise judgments, while fuzzy ranges were imposed analytically to examine uncertainty around those judgments, and Monte Carlo simulation propagated that specified uncertainty. Consistent with dual-factor theory, drivers and inhibitors are analyzed as separate hierarchies, not as opposite ends of a single normalized vector [27,28]. The stakeholder-related component hierarchy is the primary, directly elicited analysis, while PEST provides a secondary descriptive classification of the same factor priorities.

The study makes three contributions to organizational adoption research in multi-sided creator settings. First, it shifts the focal question from fan-level use or isolated platform attributes to the entertainment company's adoption decision and provides, within the identified literature, a common comparison of company experts' assessments of artist-, company-, and fandom-related conditions while preserving separate driver and inhibitor hierarchies. Second, it identifies a distinction between robust stakeholder-level priority and a concentrated set of leading mechanisms: artist-related conditions remain the highest-priority component across the evaluated panel and method checks, while some adjacent factor ranks change under plausible specifications and panel scenarios. This pattern refines coordination thinking by showing that stakeholder-level priority can remain stable even when closely competing mechanisms exchange rank. Third, the study applies established AHP/SF-AHP tools with an explicit transparency protocol that checks fuzzification, group aggregation, consistency conditioning, panel composition, PEST classification, and factor-inventory coverage. Empirically, these contributions are grounded in a pre-specified 24-factor hierarchy evaluated by company experts in the South Korean entertainment setting.

The paper proceeds as follows. Section 2 develops the theoretical background, linking multi-sided interdependence and possible cross-side asymmetry to the Korean entertainment context, organizational adoption, and dual-factor evaluation. Section 3 sets out the

factor-identification process, research framework, propositions, and SF-AHP methodology. Section 4 presents the results and robustness analyses, and Section 5 discusses the theoretical and practical implications and limitations before concluding.

2. Theoretical Background

2.1. Multi-Sided Platforms, Asymmetry, and Value Coordination

A multi-sided platform is an intermediary that enables value-creating interactions among two or more distinct, interdependent groups of participants [1,29]. Its defining feature is cross-side interdependence: the value each side draws from the platform depends on the participation and contributions of the others, so the platform's central task is to bring several sides on board and govern the terms on which they interact [30,31]. This departs from the logic of pipeline firms, which build value through a sequential chain of internal activities. A platform instead creates value by orchestrating interactions and complementary contributions it neither owns nor fully directs [2].

As they grow, platforms come to operate as ecosystems of interdependent actors whose joint activity—not the effort of any one contributor—generates value [3,4,32–34]. Interdependence, however, does not require balanced or equal contribution. Research on platform network effects shows that cross-side effects can be asymmetric and that some contributors may be especially consequential because their output attracts or retains the other sides [5–7]. In the Korean platform context, artist activity and coordinated support from entertainment companies and platform operators have been associated with channel performance and fan engagement [24]. This evidence makes artist-side concentration theoretically plausible without presupposing the empirical ordering. In fandom platforms, artists supply presence and creativity, companies supply orchestration and infrastructure, and fandoms supply attention, advocacy, participation, and spending. The empirical question is therefore how these complementary contributions are prioritized, not whether one side creates value alone.

Service-dominant logic spells out how interaction yields value. On this view, value is not manufactured and shipped by a firm but co-created through resource integration and interaction among actors, and it is realized in use, not embedded in an output [35–37]. Firms offer value propositions, while beneficiaries participate actively in the process. On a fandom platform, value emerges through interaction among artists, fandoms, and the entertainment company that coordinates the platform; no side creates it alone.

Value creation must be kept distinct from value capture. Creating value enlarges the use and exchange value available to participants; capturing value concerns how that value is appropriated across actors and levels [9–12]. Capture is not inherently corrosive: without viable appropriation, the focal firm cannot invest in infrastructure, governance, or complementary assets. Tension arises when allocation, control, or governance costs become misaligned with the continued incentives of ecosystem participants [13–15]. In fandom platforms, such frictions may involve artist workload, compensation, fan payment pressure, privacy, operating costs, capability deficits, usability, or the displacement of existing communities.

These perspectives play distinct roles in the argument. Multi-sided platform theory explains cross-side interdependence and the possibility of asymmetric network effects; organizational-adoption research identifies the entertainment company as the focal decision-maker; and dual-factor theory supports evaluating enabling and inhibiting considerations as separate sets. Service-dominant logic and value-creation/value-capture research provide interpretive lenses for how participation, governance, and appropriation can create cross-side tensions, but those constructs are not directly operationalized or tested here. Taken together, the perspectives suggest a conditional mechanism: when artist participation

supplies a central source of cross-side attraction and the company's adoption decision depends on sustaining that participation, company experts may assign greater priority to artist-related conditions on both the enabling and inhibiting sides. This mechanism is most plausible in agency-mediated arrangements in which the focal firm coordinates access, monetization, data use, participation rules, and support while remaining dependent on sustained artist participation for cross-side attraction [19,24–26,38,39]. A stable stakeholder-level ordering, however, need not imply a fixed ranking of the specific mechanism—workload, compensation, privacy, communication, or monetization—through which that coordination focus is expressed.

2.2. Fandom Platforms in the Korean Entertainment Context

Fandom platforms are best read against the wider fan economy—the economic and participatory activity generated through interactions within fandoms [40,41]. Highly committed fans contribute not only direct spending but also attention, advocacy, circulation, data, and community participation [42–44]. In the Korean entertainment industry, these activities are increasingly organized through company-governed platforms that integrate communication, content, community, membership, and commerce [16–19,22,25]. This arrangement can strengthen access and global coordination, but it also places affective relationships and fan practices within technical and commercial rules designed by entertainment companies.

A fandom platform is an online environment where fans access artist-related content and services and carry out fan activities, typically pairing personalized communication and live video with community and commerce functions [22]. These platforms first took shape in South Korea as fan interaction migrated from online communities and live-streaming services [45] to dedicated platforms such as Weverse and Bubble. The artist–fan relationship is consequently both a central resource and a site of labor and governance: interaction is structured through interfaces, contracts, subscriber-linked incentives, company support, and organizational gatekeeping [19,24–26,46].

Research on fandom platforms is substantive but addresses different units and questions. Existing work analyzes particular platforms, user experience, fan practices and participatory branding, communication consumption, artist labor, marketing, or behavioral outcomes [16–26,47]. Even the available priority analysis focuses on user-facing service attributes [21]. Within the identified literature, no study uses a common set of factors to compare the relative priority of artist-, company-, and fandom-related considerations in a company-level adoption decision while maintaining separate driver and inhibitor hierarchies and reporting uncertainty in judgments and sensitivity to panel composition. This common priority comparison is the specific empirical gap addressed here.

2.3. Organizational Adoption and Dual-Factor Evaluation

Organizational adoption is an ex ante managerial decision made under incomplete information about expected consequences, available resources, control, readiness, and external conditions. Organizational-adoption and executive technology-adoption research shows that organizational readiness, perceived control, expected favorable and unfavorable consequences, and external pressures can enter this judgment [48–50]. In this study, the decision belongs to the entertainment company, while artist- and fandom-related conditions matter because they affect the feasibility and attractiveness of that organizational choice.

This approach aligns with the dual-factor model of technology use [27,28], which treats enablers and inhibitors as qualitatively distinct beliefs, not opposite ends of one continuum. The absence of an inhibitor does not itself create an incentive, and the absence of an enabler does not necessarily prevent adoption. The logic traces back to Herzberg's

motivation–hygiene theory [51], which Cenfetelli's model adapts to technology adoption and use.

In keeping with this model, we do not treat drivers and inhibitors as symmetric causal determinants of adoption or as direct measures of value creation and value capture. They are candidate conditions that company-side experts evaluate as encouraging or constraining an organizational adoption decision. Drivers include anticipated benefits such as monetization, promotion, communication, data, global reach, and service integration; inhibitors include concerns arising from allocation, coordination, capability, labor, privacy, cost, usability, community, and governance. Separate normalization preserves this distinction and prevents the two sets from becoming a zero-sum scale. Importantly, the Artist and Fandom blocks represent company experts' assessments of conditions associated with those stakeholders, not direct measures of artists' or fans' own preferences.

Table 2 organizes the conceptual domains that informed the six driver and inhibitor blocks associated with the three stakeholder-related condition blocks. These source-level concepts document the literature background for identifying and consolidating candidate adoption conditions, while the 24 operational factors used in the expert elicitation are reported separately in Table 3.

Table 2. Literature domains informing the six pre-specified factor blocks.

Stakeholder-Related Block	Source-Level Orientation	Illustrative Concept Domains	Related Pre-Specified Factor Block	Representative Sources
Artist	Favorable	Monetization, promotion, communication convenience, and feedback	Artist-driver block (D1–D4)	[16,22,52–54]
Artist	Unfavorable	Relational workload and fatigue, agency/platform support, revenue allocation, and privacy boundaries	Artist-inhibitor block (H1–H4)	[5,19,46,53]
Entertainment Company	Favorable	Revenue diversification, global expansion, consumer data, and integrated fandom management	Company-driver block (D5–D8)	[22,52–55]
Entertainment Company	Unfavorable	Development and operating costs, external-artist acquisition, consumer privacy, and platform-operating capability	Company-inhibitor block (H5–H8)	[21,53,55,56]
Fandom	Favorable	Direct artist communication, exclusive content, integrated information, and content translation	Fandom-driver block (D9–D12)	[16,20,22,52,53,55,56]
Fandom	Unfavorable	Payment pressure, community displacement, usage fatigue, and platform complexity	Fandom-inhibitor block (H9–H12)	[21,22,55]

Note: This table summarizes block-level concept domains. Factor-level source mappings and source details for the 24 operational factors are reported in Supplementary File S1.

Table 3. Pre-specified driver and inhibitor factors used in the SF-AHP elicitation.

Driver Code	Driver Factor	Inhibitor Code	Inhibitor Factor
D1	Stable monetization	H1	Rise in artists' fatigue level
D2	Use as a promotion channel	H2	Lack of support from the agency
D3	Convenient communication tools for artists	H3	Insufficient revenue sharing

Table 3. *Cont.*

Driver Code	Driver Factor	Inhibitor Code	Inhibitor Factor
D4	A way of collecting feedback from fandom	H4	Artist privacy risks
D5	A way of increasing revenue and diversifying the revenue model	H5	High cost of building and operating platform
D6	Ease of global expansion	H6	Difficulty of attracting external artists
D7	Acquisition of consumer data	H7	Consumer privacy risks
D8	Enhanced ability to lock in and manage the fandom	H8	Lack of experience operating platforms
D9	Direct communication access for fandoms	H9	Excessive payment inducements
D10	Access to exclusive content	H10	Backlash from the decline of the existing fandom communities
D11	Integrated delivery of artist-related news and information	H11	Rise in fandoms' fatigue level
D12	Provision of content translation	H12	Complexity of the platforms

Note: Factor labels were fixed before survey administration. Full operational definitions are provided in Appendix A.1, and factor-level source mappings are reported in Supplementary File S1.

2.4. Platform Governance and the Macro-Environment

To analyze the forces shaping adoption, we organize the drivers and inhibitors through two complementary lenses. The first decomposes the company's adoption judgment into artist-, entertainment-company-, and fandom-related condition blocks. These correspond to interdependent sides of the platform ecosystem, but the elicited weights represent company experts' assessments of conditions associated with those stakeholders, not stakeholder preferences themselves. This directly elicited component hierarchy is the primary analytical frame. Its weights indicate how the expert panel prioritizes the evaluated adoption conditions and do not directly measure the amount of value produced by each side.

The second lens places the same factors in the macro-environment in which the platforms operate, using the PEST framework of political, economic, social, and technological conditions. Platform architecture, governance, and environmental conditions coevolve, and governance choices shape the balance between co-created value and operating or participation costs [15,38,39]. PEST can therefore contextualize the factor set by organizing regulatory, economic, social, and technological mechanisms that may shape anticipated benefits and participation costs. Regulation and market governance influence data-use rights, privacy obligations, contractual control, and the allocation of platform responsibilities. Monetization pressure and infrastructure requirements shape economic viability, while technological conditions affect service integration, scalability, security, and the capabilities needed to coordinate participation. PEST is therefore used as a contextual classification of the factor set rather than as a causal hierarchy.

The two lenses have different methodological status. The Artist–Company–Fandom structure constituted the pre-specified elicitation hierarchy used in the survey and SF-AHP analysis. The same factors were also assigned to a secondary, non-elicited PEST classification outside that hierarchy. Accordingly, component weights are derived from direct expert comparisons within the hierarchy, whereas PEST summaries are calculated by aggregating the estimated within-set factor priorities according to the PEST mapping.

3. Methodology

3.1. Methodological Approach and Scope

The evidence gap addressed by this method is decision-specific. Platform-generated behavioral and transaction data can be abundant, but comparable public evidence on entertainment companies' ex ante adoption judgments, implementation trade-offs, contracts, investment choices, and cross-side operating consequences is limited or proprietary.

In this study, fandom-platform adoption refers broadly to an entertainment company's organizational decision concerning whether and how to establish or participate in a fandom-platform arrangement while considering anticipated implementation and operating consequences. The elicitation task was framed at this broad company-adoption level rather than as separate proprietary-build, third-party participation, or continued-operation scenarios. SF-AHP is used to structure relative priorities within this pre-specified decision hierarchy using judgments from domain professionals in strategy, business development, or platform operation.

The resulting priorities summarize how the company-expert panel evaluates the relative importance of the specified adoption conditions under analytical uncertainty. They are interpreted as decision-analytic priorities within the observed panel and hierarchy rather than as causal or population-representative estimates.

3.2. Framework and Propositions

3.2.1. Research Model

Figure 1 presents the research model. A set of 12 drivers and 12 inhibitors was consolidated before data collection through a broad, iterative review of academic, Korean institutional, industry, and press sources. The factors were organized into separate driver and inhibitor SF-AHP hierarchies, each containing three directly elicited stakeholder-related components—Artist, Entertainment Company, and Fandom—and four factors within each component. Respondents directly compared the components and the factors within each component, and the resulting component and global factor priorities were estimated and normalized separately within the driver and inhibitor sets. Independently of these elicited comparisons, the same factors were classified into PEST categories. The PEST mapping was then used to aggregate the estimated within-set factor priorities; PEST did not constitute an additional elicited hierarchy level. Source traceability and inventory coverage for the pre-specified factor set are documented in Appendix A.2 and Supplementary File S1.

3.2.2. Pre-Specified Stakeholder-Related Component Hierarchies

We analyze the fandom-platform decision by organizing drivers and inhibitors into three stakeholder-related condition blocks: Artist, Entertainment Company, and Fandom. Artists are entertainers who seek to engage their fandoms through these platforms; the group spans not only K-pop idols but also singers, actors, and models. Entertainment companies are the focal decision-making organizations that manage these artists within the South Korean media and entertainment industry; here, this includes the four major idol agencies—HYBE, SM Entertainment, JYP Entertainment, and YG Entertainment—together with companies representing actors and models. Fandoms are groups of individuals who consume artist-related content through the platforms. Because respondents are company professionals, the "Artist" and "Fandom" labels denote company experts' assessments of conditions associated with those stakeholders, not priorities elicited from artists or fandoms themselves.

3.2.3. Secondary PEST Classification

PEST groups business-environment considerations into political, economic, social, and technological categories [57]. In this study, it provides a secondary classification external to the elicited AHP hierarchy. Each factor is assigned according to its dominant environmental or institutional mechanism in the South Korean market. Political assignments apply when formal institutions, public policy, regulation, legal rights, enforcement, or market governance constitute that dominant mechanism, as documented in a brief rationale.

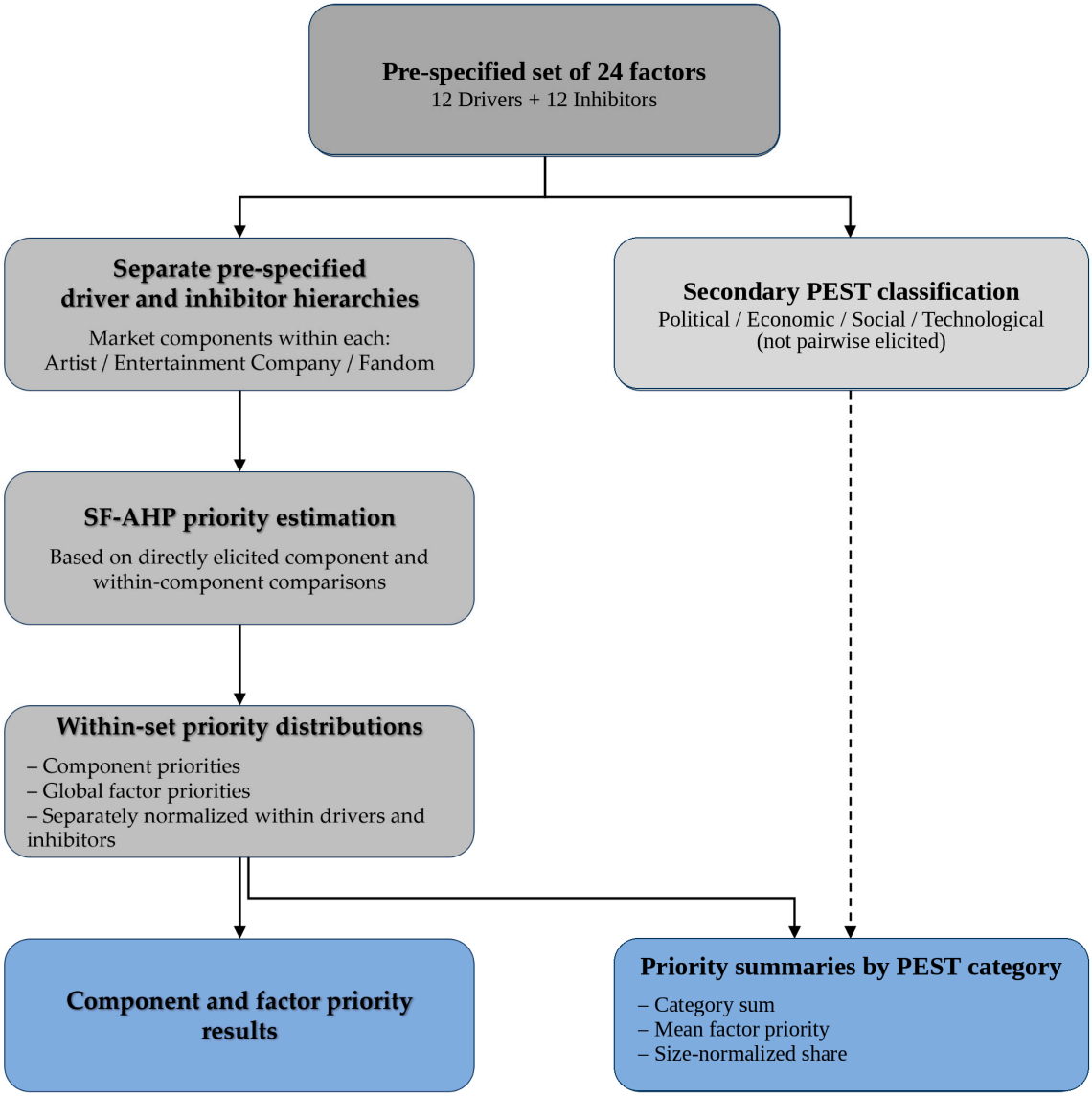


Figure 1. Research model for the separate SF-AHP hierarchies and secondary PEST analysis. Respondents provided component-level and within-component pairwise comparisons separately for drivers and inhibitors. PEST categories were not pairwise elicited; the classification was used to aggregate the estimated within-set factor priorities. The direct driver–inhibitor comparison collected in the survey was excluded from the primary factor-priority analysis.

3.3. The Stochastic Fuzzy Analytic Hierarchy Process (SF-AHP) Framework

To analyze the qualitative conditions associated with fandom-platform adoption, we employ the Stochastic Fuzzy Analytic Hierarchy Process (SF-AHP). The Analytic Hierarchy Process structures pairwise priority judgments [58]; fuzzy-set and fuzzy-AHP extensions represent analytically specified imprecision [59–62]; and stochastic or probabilistic formulations characterize uncertainty in derived priorities [63,64]. In the present implementation, Monte Carlo simulation propagates fuzzy uncertainty subject to an explicit consistency constraint, while sensitivity to panel composition, fuzzification, and group aggregation is evaluated separately. The methodological value of this application lies in combining the established SF-AHP framework with an explicit robustness and transparency protocol spanning panel composition, fuzzification, consistency conditioning, group aggregation, and classification sensitivity.

3.3.1. Hierarchy Design and Fuzzy Pairwise Comparison

The survey was organized into separate driver and inhibitor branches. Within each branch, experts first compared the three stakeholder-related components (Artist, Entertainment Company, and Fandom) and then compared four sub-factors within each component. The instrument also included one direct top-level comparison between drivers and inhibitors. Each respondent therefore completed 43 pairwise comparisons across nine matrices: one direct driver–inhibitor comparison, two 3×3 component matrices, and six 4×4 sub-factor matrices.

Because dual-factor theory treats drivers and inhibitors as qualitatively distinct constructs, the primary analysis does not combine the 24 factors into a single zero-sum vector. The direct top-level driver–inhibitor item is excluded from factor-priority calculations, proposition assessment, and substantive cross-set interpretation. The factor analysis uses eight nontrivial matrices and 42 comparisons per respondent, with the 12 driver priorities and 12 inhibitor priorities separately normalized to sum to one.

The stakeholder-related component level was directly elicited and therefore forms the primary AHP structure. PEST is not an additional level in the AHP hierarchy. The mapping is used only to aggregate the estimated within-set factor priorities.

Respondents selected crisp values on the conventional Saaty 1–9 pairwise-comparison scale without directly reporting fuzzy ranges. For the SF-AHP analysis, each observed crisp judgment was mapped after data collection to a triangular fuzzy number (TFN). The primary mapping is $1 = (1, 1, 1), 2 = (1, 2, 3), 3 = (2, 3, 4), 4 = (3, 4, 5), 5 = (4, 5, 6), 6 = (5, 6, 7), 7 = (6, 7, 8), 8 = (7, 8, 9)$, and $9 = (8, 9, 9)$, with reciprocal judgments represented as $(l, m, u)^{-1} = (1/u, 1/m, 1/l)$. This one-step bounded conversion is used in applied fuzzy-AHP work [65], while TFN-based fuzzy AHP is grounded in established formulations [60–62]. Because respondents did not specify fuzzy ranges, the TFN width is an analyst-imposed uncertainty specification, not empirically observed respondent-specific uncertainty. Robustness checks therefore use the original crisp judgments and the published $d = 1$ and $d = 2$ scale specifications of [66], where d indexes increasing fuzzy spread under that scale family's discrete mapping rules. The complete primary and alternative mappings are reported in Table A9 and in the reproducibility package. The relative importance of criterion j over criterion i, as assessed for the kth expert, is represented as

$$\tilde{a}_{ij}^{(k)} = \left(l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}\right) \tag{1}$$

where $l_{ij}^{(k)}$, $m_{ij}^{(k)}$, and $u_{ij}^{(k)}$ denote the lower bound, modal (most plausible) value, and upper bound of the fuzzy number, respectively. This pairwise comparison matrix must satisfy the following reciprocal property:

$$\tilde{a}_{ji}^{(k)} = \left(\frac{1}{u_{ij}^{(k)}}, \frac{1}{m_{ij}^{(k)}}, \frac{1}{l_{ij}^{(k)}}\right) \tag{2}$$

3.3.2. Defuzzification and Consistency Verification

For consistency verification, the fuzzy numbers are converted into single crisp values through a process called defuzzification. This study utilizes the Graded Mean Integration (GMI) method, a widely used technique, for this purpose. The formula is as follows:

$$P(\tilde{a}_{ij}^{(k)}) = \frac{l_{ij}^{(k)} + 4m_{ij}^{(k)} + u_{ij}^{(k)}}{6} \tag{3}$$

A crisp pairwise comparison matrix, $A^{(k)}$, is constructed from these single values, where $a_{ij}^{(k)} = P(\tilde{a}_{ij}^{(k)})$.

Next, the logical consistency of each expert's judgments is verified. The Consistency Ratio (CR) is calculated from the maximum eigenvalue ($\lambda_{max}^{(k)}$) of the matrix $A^{(k)}$:

$$CR^{(k)} = \frac{\lambda_{max}^{(k)} - n}{RI(n) \times (n-1)} \quad (4)$$

where n is the size of the matrix, and RI is the Random Index proposed by Saaty [58] (RI = 0.58 for order-3 matrices and RI = 0.90 for order-4 matrices). A completed response matrix was admissible only if CR < 0.10. Across the 28 completed respondents and eight nontrivial matrices, the analysis contains 224 expert-by-matrix final CR values; all satisfy the threshold, with a mean CR of 0.0583 and a maximum of 0.09999. These low final CR values should be interpreted in light of the survey design: I Make It AHP (Decision Science Co., Ltd.; https://imakeit.kr/info/index.html) calculated section-level consistency in real time, prompted respondents to reconsider judgments when the threshold was not met, and prevented progression until the relevant section passed. Thus, the observed CR distribution reflects both expert judgments and consistency enforcement rather than an unconstrained measure of natural expert consistency. The export preserves the final observed judgment fields and completion pattern, allowing complete and incomplete records to be distinguished, but it does not preserve warning counts, CR values before respondent adjustment, or matrix-level judgment-adjustment histories. These process measures are therefore unavailable. The direct top-level driver–inhibitor comparison has no applicable CR and is excluded from the factor-priority analysis.

3.3.3. Integrating Uncertainty via Monte Carlo Simulation

The primary Monte Carlo analysis uses 10,000 iterations to propagate the analyst-specified fuzzy uncertainty around the completed expert judgments while preserving the same consistency standard applied to the observed responses, consistent with stochastic and probabilistic AHP reasoning [63,64]. Equal expert weighting and aggregation of individual priorities (AIP) are used in the primary specification because no external expert-level reliability measure was collected. Alternative group-aggregation and fuzzification specifications are evaluated as robustness checks. The procedure is as follows:

1. TFN sampling and reciprocity: For each expert and pairwise judgment represented by TFN (l, m, u), a crisp comparison is sampled from the corresponding triangular distribution. The reciprocal comparison is set deterministically as its inverse, preserving matrix reciprocity.
$$a_{ij}^{(k,t)} \sim \text{Triangular}\left(l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}\right) \quad (5)$$
2. Consistency-conditioned retention: A sampled expert matrix is retained only when its CR is below 0.10; otherwise, the complete matrix is redrawn. This rejection-sampling step prevents the simulation from introducing judgment structures that would have been excluded from the observed sample. In a diagnostic unconstrained independent-draw procedure, only 88.1% of sampled expert–node matrices met CR < 0.10 on average, confirming that explicit consistency conditioning is consequential.
3. Expert-level priorities and group aggregation: The principal eigenvector of each retained sampled matrix is normalized to sum to one. Under the primary equal-weight AIP specification, the 28 expert priority vectors are averaged within each iteration. Component and sub-factor priorities are combined multiplicatively within the driver hierarchy and within the inhibitor hierarchy, and each hierarchy is normalized separately. As an aggregation sensitivity check, a crisp aggregation-of-individual-

judgments (AIJ) specification geometrically averages each pairwise judgment across respondents before deriving the group priority vector; AIP and AIJ are established alternatives for group AHP [67].

$$\gamma_k^{(t)} \sim \text{Beta}(\alpha, \beta) \tag{6}$$

4. Alternative expert-weight sensitivity: Equal expert weighting is used in the primary analysis because no observed expert-specific reliability measure was collected. Sensitivity analyses compare equal weighting with Beta(1,1), Beta(2,1), Beta(5,1), and Beta(8,1) expert-weight distributions. These specifications leave the mean ranking virtually unchanged but alter interval width; they are interpreted as alternative variance-inflation assumptions, not measured reliability corrections.

$$\gamma_k^{(t,\text{norm})} = \frac{\gamma_k^{(t)}}{\sum_{k=1}^{K} \gamma_k^{(t)}} \tag{7}$$

5. Uncertainty summaries: For each factor and component, the retained simulation draws provide the mean, standard deviation, percentile-based 95% simulation interval, mean rank, the proportion of retained draws ranked first, and the proportion appearing in the top three. These intervals describe variation induced by TFN sampling conditional on the observed panel and should not be interpreted as population confidence intervals.

$$W^{(t)} = \sum_{k=1}^{K} \gamma_k^{(t,norm)} w^{(k,t)} \tag{8}$$

6. Sensitivity to panel composition is evaluated separately using 10,000 respondent-level bootstrap samples and 10,000 firm-cluster resamples. The former resamples the 28 experts; the latter resamples the eight observed firms and retains all respondents belonging to each selected firm. We also exclude the largest firm cluster entirely, apply equal firm weighting, and perform leave-one-firm-out analyses. Because the cluster analysis contains only eight observed firms, its percentile ranges are interpreted as cluster-resampling sensitivity intervals, not conventional population confidence intervals; the deterministic leave-one-firm-out, largest-firm-exclusion, and equal-firm-weight checks receive particular interpretive weight.
7. The analysis therefore examines four distinct robustness dimensions separately: method-specification sensitivity, including the imposed fuzzy specification, crisp AHP-AIP, geometric-mean AIJ, and alternative TFN mappings; consistency-conditioned sampled-matrix validity; respondent and firm composition; and secondary PEST classification and aggregation choices. Each is evaluated with a separate diagnostic rather than being combined in one interval.

3.3.4. Primary Component Propositions and Exploratory PEST Questions

Within multi-sided fandom platforms, artist participation supplies the relational presence and creator output around which fan attention, communication, and platform-specific content are organized. Because these contributions can generate asymmetric cross-side attraction, artist-related enabling conditions may receive greater priority in a company's adoption judgment than company- or fandom-related conditions. This yields the first proposition:

Proposition 1. *Among the stakeholder-related condition blocks in the fandom-platform decision, artist-related factors will be a stronger driver than entertainment-company or fandom-related factors.*

Because the PEST categories were not directly compared by respondents, the macro-environmental analysis is treated as exploratory, with no proposition verdict assigned. Relational and community-facing functions provide a basis for asking whether Social considerations appear prominent on the driver side and whether that pattern persists across cumulative and factor-count-adjusted aggregation:

EQ1. *How do driver priorities distribute across Political, Economic, Social, and Technological categories under cumulative and category-size-adjusted summaries?*

The same relational centrality may also concentrate constraints on the artist side. Sustained platform participation creates workload, agency-support, compensation, and privacy-boundary demands; if these conditions are not manageable, the platform may struggle to maintain artist participation on which fan engagement depends. This motivates the second directly elicited component proposition:

Proposition 2. *Among the stakeholder-related condition blocks in the fandom-platform decision, artist-related factors will be a stronger inhibitor than entertainment-company or fandom-related factors.*

On the inhibitor side, economic viability and distributional frictions—including operating cost, revenue sharing, difficulty attracting external artists, and fan payment pressure—provide one plausible macro-environmental pattern. Because PEST remains a secondary non-elicited overlay, this possibility is examined descriptively, without a support verdict:

EQ2. *How do inhibitor priorities distribute across Political, Economic, Social, and Technological categories under cumulative and category-size-adjusted summaries?*

3.3.5. Inferential Scope

The simulation intervals reported with each priority summarize dispersion across 10,000 CR-conditioned Monte Carlo iterations. They describe variation induced by the specified TFN sampling conditional on the observed panel and should not be interpreted as population confidence intervals or significance tests. Sensitivity to panel composition is evaluated separately with respondent and firm-cluster percentile resampling intervals; because recruitment was non-probabilistic and only eight firms were observed, these intervals are used as sensitivity diagnostics rather than population-inferential confidence intervals. We reserve proposition support for the two directly elicited component orderings that remain stable under the relevant panel checks. PEST summaries answer exploratory questions and are interpreted descriptively, with sign-crossing or aggregation-sensitive gaps treated as evidence against a stable category dominance rather than as formal hypothesis-test outcomes.

3.4. Identification of Drivers and Inhibitors

3.4.1. Factor Identification and Pre-Survey Specification

Dual-factor theory treats adoption drivers and inhibitors as distinct evaluative constructs rather than as opposite endpoints of a single continuum [27,28]; accordingly, the absence of a driver does not imply the presence of an inhibitor, nor does the absence of an inhibitor constitute a driver. The two sets were therefore elicited in separate hierarchies and normalized separately within their respective sets. Table 2 summarizes the conceptual background for the six factor blocks, whereas Table 3 reports the 24 operational factors consolidated and fixed before data collection; Table A1 defines each item, and Table 4 shows the stakeholder-related condition blocks used for local pairwise comparisons.

Table 4. Pre-specified stakeholder-related condition blocks in the SF-AHP elicitation hierarchy.

	Artist	Entertainment Company	Fandom
Drivers	D1, D2, D3, D4	D5, D6, D7, D8	D9, D10, D11, D12
Inhibitors	H1, H2, H3, H4	H5, H6, H7, H8	H9, H10, H11, H12

The factor-identification process drew on academic work on fandom platforms, the fan economy, creator and community platforms, and organizational technology adoption, together with Korean government-affiliated reports, industry materials, and press coverage. Candidate considerations were retained when they represented a distinct company-level adoption consideration within one of the three pre-specified components, consolidated when their substantive mechanisms overlapped, and excluded when they were generic to digital services, duplicated another item, or fell outside the company-level adoption decision. The 24-factor inventory was fixed before data collection. The underlying development process was broad and iterative rather than a prospectively logged systematic review: surviving source materials allow 11 records to be traced to the pre-survey factor-development process, one only at the issue level, and do not provide a complete screening count or bounded search period. To strengthen source traceability for factors with weaker surviving documentation without altering the pre-specified inventory, a separately dated corroboration audit conducted on 26 July 2026 examined H2, H3, H4, and H8 and recorded 48 factor-level screening events (22 included and 26 excluded), 18 unique included publications, and 23 final factor–source mappings. Full search terms, screening records, and source mappings are provided in Appendix A.2 and Supplementary File S1.

A subsequent independent coverage and omission review completed on 28–29 July 2026 assessed whether the fixed inventory omitted broad concept domains while withholding factor weights, rankings, PEST assignments, propositions, category counts, and analytical results. The academic reviewer was an associate professor of business administration; the industry reviewer had private-equity portfolio-company management experience together with entertainment-company investment and operating experience. Neither reviewer identified a material or critical cross-cutting omission. They nevertheless flagged possible D7/D8 and H5/H8 overlap, underrepresented uncertainty about sustained artist participation and differentiated paid value, and scope concerns involving H4, D8, and H10. These observations define specific boundaries for interpreting the inventory and are documented in Supplementary File S1 (sheet 01_Coverage_Omission_Analysis).

3.4.2. Classification of Drivers and Inhibitors

Before survey administration, the 12 drivers and 12 inhibitors were organized into fixed Artist–Company–Fandom component blocks that constituted the elicitation hierarchy. Respondents made local pairwise comparisons within these blocks. The initial PEST mapping was also specified before survey administration but remained outside the elicited AHP hierarchy. A subsequent independent classification procedure assessed the reproducibility of that mapping, and the reconciled mapping was used only to aggregate the estimated within-set factor priorities.

A second coder who had not participated in factor development, survey administration, or quantitative analysis independently classified the 24 factors. The coder was a doctoral researcher in business/business analytics employed in a platform-related role and reported familiarity with platform business, information systems, and quantitative research methods. The coder received the factor labels and definitions, a common bilingual PEST codebook, balanced factor-independent practice examples, and a neutral South Korean context brief, but did not receive the manuscript, original PEST assignments, factor weights, rankings, propositions, category counts, or analytical results. Classification followed the di-

rect and dominant substantive mechanism of each factor rather than possible downstream commercial consequences. All 24 classifications were completed before any study item was discussed with the research team.

Agreement on primary PEST codes was assessed before discussion using percentage agreement and unweighted Cohen's kappa. Both coding records were locked before disagreements were reconciled against the original factor definitions, common codebook, and dominant-mechanism rule, without reference to factor weights, primary component-proposition results, or exploratory PEST summaries. The resulting consensus classification was used for all exploratory PEST aggregation. Alternative codes and confidence ratings were retained as diagnostic information but were not counted as agreement.

The 24 factors were organized into six four-item driver and inhibitor blocks across the three stakeholder-related components within the pre-specified hierarchy (Table 4). The artist-related block contains conditions associated with artist participation in the company's adoption judgment. Its drivers are stable monetization (D1), use as a promotion channel (D2), convenient communication tools for artists (D3), and a way of collecting feedback from fandom (D4). Its inhibitors are a rise in artists' fatigue level (H1), lack of support from the agency (H2), insufficient revenue sharing (H3), and artist privacy risks (H4). These weights represent company experts' assessments of artist-related conditions rather than priorities elicited from artists themselves.

The entertainment-company-related block concerns business feasibility and operating demands in the company's adoption judgment. Drivers include a way of increasing revenue and diversifying the revenue model (D5), ease of global expansion (D6), acquisition of consumer data (D7), and an enhanced ability to lock in and manage the fandom (D8). Inhibitors include high costs of building and operating the platform (H5), difficulty attracting external artists (H6), consumer privacy risks (H7), and lack of experience operating platforms (H8).

The fandom-related block contains conditions associated with fan access and experience as assessed by company experts. Drivers include direct communication access for fandoms (D9), access to exclusive content (D10), integrated delivery of artist-related news and information (D11), and content translation (D12). Inhibitors include excessive payment inducements (H9), backlash from the decline of existing fandom communities (H10), a rise in fandom fatigue (H11), and platform complexity (H12). These weights are not presented as fandom preferences.

Table 5 presents the PEST classification used in the analysis. Because PEST is a secondary overlay, this classification does not alter the Artist–Company–Fandom hierarchy or any SF-AHP weight.

Table 5. PEST classification of the 24 factors.

	Political	**Economic**	**Social**	**Technological**
Drivers	D7	D1, D5	D2, D4, D9, D10	D3, D6, D8, D11, D12
Inhibitors	H7	H3, H5, H6, H9	H1, H2, H4, H10	H8, H11, H12

Political factors are the acquisition of consumer data (D7) and consumer privacy risks (H7), reflecting formal data-use rights, obligations, and governance. Economic factors include stable monetization (D1), increasing revenue and diversifying the revenue model (D5), insufficient revenue sharing (H3), high platform costs (H5), difficulty attracting external artists (H6), and excessive payment inducements (H9).

Social factors comprise use as a promotion channel (D2), collecting fandom feedback (D4), direct communication access (D9), access to exclusive content (D10), artist fatigue

(H1), lack of agency support (H2), artist privacy risks as a relational-boundary concern (H4), and backlash associated with existing fandom communities (H10).

Technological factors include convenient communication tools (D3), ease of global expansion through app-based delivery (D6), fandom management capability (D8), integrated news delivery (D11), translation (D12), lack of platform-operating experience (H8), fandom fatigue associated with continuous platform experience (H11), and platform complexity (H12).

3.4.3. Integration of SF-AHP Priorities and Secondary PEST Analysis

SF-AHP was used only for the two directly elicited hierarchies. The stakeholder-related component dimension forms the AHP structure, whereas the PEST dimension provides a secondary classification used to aggregate the estimated factor priorities. Accordingly, priorities are not recomputed through a second PEST hierarchy. PEST category sums are reported alongside mean factor priorities and size-normalized summaries to distinguish cumulative category weight from the mechanical effect of unequal category sizes. Figure 2 summarizes the cross-classification of the driver and inhibitor factors by pre-specified component and secondary PEST category.

(a) Drivers

Secondary PEST category

Stakeholder-related component	Political	Economic	Social	Technological
Artist		D1	D2, D4	D3
Entertainment Company	D7	D5		D6, D8
Fandom			D9, D10	D11, D12

(b) Inhibitors

Secondary PEST category

Stakeholder-related component	Political	Economic	Social	Technological
Artist		H3	H1, H2, H4	
Entertainment Company	H7	H5, H6		H8
Fandom		H9	H10	H11, H12

Figure 2. Cross-classification of (**a**) driver and (**b**) inhibitor factors by pre-specified component and secondary PEST category. Cell placement indicates classification only and does not represent priority magnitude. The PEST assignments reflect the reconciled consensus mapping.

3.5. Data Collection and Analytical Assessment

3.5.1. Data Collection

The participant-facing study notice framed the task as evaluating the relative importance of pre-defined factors that drive or inhibit the adoption of fandom platforms by Korean entertainment companies. Respondents were instructed to compare two factors at a time, and item explanations were available through the survey model interface. The instrument contained 12 pre-defined drivers and 12 pre-defined inhibitors and did not present proprietary platform development, participation in an existing third-party platform, and continued operation as separate decision scenarios. Pairwise comparisons were made using Saaty's 9-point scale. Each completed respondent provided 43 comparisons across nine matrices: one direct driver–inhibitor comparison, two 3×3 component matrices, and six 4×4 sub-factor matrices. The factor-priority analysis uses 42 comparisons across the eight component and sub-factor matrices; because dual-factor theory treats the two constructs as qualitatively distinct, the direct driver–inhibitor item is excluded from factor-priority calculations and substantive cross-set interpretation. Participants were recruited purposively through professional networks and referrals. Eligibility required employment at an entertainment company with an Artists and Repertoire function and a strategy, business-development, or platform-operation role relevant to firm-level adoption decisions.

Data were collected with I Make It AHP. The system calculated section-level consistency ratios in real time, prompted respondents to reconsider judgments when the threshold was not met, and prevented progression until the relevant section satisfied the consistency criterion; exported matrices were independently recalculated before analysis. The raw export shows 28 complete records containing all required pairwise judgments; these 28 complete records constitute the analytical panel. Two additional records are partial and do not contain the full set of required judgments, so they are incomplete rather than complete records subsequently excluded for analytical inconsistency. Their reasons for discontinuation were not recorded. The export preserves this completion pattern and the final observed judgments but not the sequence of consistency warnings, CR values before respondent adjustment, or matrix-level judgment-adjustment histories.

The panel was assembled for a structured industry-expert priority analysis rather than population representation. Recruitment established occupational relevance for the included participants through employment and role criteria relevant to firm-level platform decisions. Detailed respondent-level job titles, responsibility level, and career histories were not retained in the analytical AHP response dataset. Topic familiarity was an eligibility consideration during recruitment but was not measured on a standardized respondent-level scale, and direct involvement in specific adoption or operation episodes was not separately measured.

Available recruitment-stage background information is used only to describe the panel in aggregate and is not linked to individual AHP judgments in the analysis or public repository. Functional-area information is reportable for 19 of the 28 completed respondents: nine worked in strategy and ten in business development or platform operation; the latter two categories are combined because one underlying category was very small, reducing indirect re-identification risk. Industry-experience bands are reportable for 26 respondents: twelve had at least five but fewer than ten years of industry experience, and fourteen had at least ten but fewer than fifteen years. The remaining functional-area and industry-experience information is reported as unavailable for aggregate reporting; no missing characteristics were inferred or imputed. Table 6 reports these aggregate characteristics together with the anonymized firm distribution.

Table 6. Respondent distribution by anonymized firm and aggregate professional profile.

Panel A. Firm Distribution		
Firm Code	**Classification of Affiliation**	**Number of Respondents**
Firm A	Idol	10
Firm B	Idol, singer	6
Firm C	Idol, singer	4
Firm D	Idol, singer	2
Firm E	Idol	2
Firm F	Actor	2
Firm G	Other entertainment	1
Firm H	Other entertainment	1
Total	**-**	**28**
Panel B. Aggregate professional profile		
Characteristic	**Category**	**Number of respondents**
Functional area	Strategy	9
Functional area	Business development/platform operation	10
Functional area	Not available for aggregate reporting	9
Industry experience	5 to <10 years	12
Industry experience	10 to <15 years	14
Industry experience	Not available for aggregate reporting	2

The anonymous online questionnaire collected no names, telephone numbers, email addresses, or other direct personal identifiers. Company and job-function eligibility were checked during recruitment; some participants were approached through professional introducers, but introducers did not receive survey responses and were not part of the analytical data. Detailed company names, job titles, and career histories were not retained in the analytical AHP response dataset. Available recruitment-stage background information used for aggregate panel description remained separate from the analytical AHP response file, and the reported professional characteristics were not linked to individual AHP judgments in the analysis or public repository. An anonymized firm code was retained solely for aggregate sample description and firm-composition sensitivity analyses, and firms are reported as Firm A through Firm H.

3.5.2. Proposition and Exploratory PEST Assessment

The two primary component propositions are evaluated using separately normalized driver and inhibitor priorities. In this study, proposition support denotes a pre-specified within-panel component ordering that remains stable across the uncertainty and panel-composition checks described below. The secondary PEST questions are treated descriptively because respondents did not directly compare the PEST categories.

For Proposition 1 and Proposition 2, the three stakeholder-related condition blocks are compared using the directly elicited component priorities within the driver and inhibitor hierarchies. A component proposition is treated as supported within the evaluated panel and hierarchy only when the target component has a positive gap over its strongest competitor and the 95% respondent-resampling and firm-cluster sensitivity intervals for that gap remain above zero.

$$W_{\text{Artist, Drivers}} = \sum_{i \in \{\text{D1,D2,D3,D4}\}} \mathbb{E}[W_i] \tag{9}$$

For EQ1 and EQ2, PEST is treated as a secondary descriptive overlay. We report both the cumulative category sum and a category-size-adjusted measure. The latter first calculates the mean factor weight within each nonempty PEST category and then renormalizes those means across categories. These two summaries answer different descriptive questions—cumulative weight represented by the factors assigned to a category versus average weight per assigned factor—and neither is treated as a directly elicited PEST preference. Reporting both reduces the risk that a category with more assigned factors is mechanically interpreted as dominant.

$$S_{s,c} = \sum_{i \in I_{s,c}} w_{s,i} \tag{10}$$

$$A_{s,c} = \frac{\frac{S_{s,c}}{n_{s,c}}}{\sum_{c' \in C_s} \frac{S_{s,c'}}{n_{s,c'}}} \tag{11}$$

where s indexes the driver or inhibitor set, c indexes a nonempty PEST category, $I_{s,c}$ is the set of factors assigned to category c, $n_{s,c}$ is its factor count, $w_{s,i}$ is the separately normalized within-set priority of factor i, $S_{s,c}$ is the raw category sum, and $A_{s,c}$ is the category-size-adjusted share.

Monte Carlo simulation intervals describe variation induced by the specified TFN sampling conditional on the observed panel. Respondent and firm-cluster percentile intervals describe sensitivity to resampling the observed panel; they are not used as conventional population confidence intervals. Component-proposition assessment follows the stability

rule above. PEST results are reported as classification- and aggregation-sensitive descriptive contrasts rather than as supported or unsupported propositions.

4. Results

This section reports the SF-AHP findings in four parts. We first present the separately normalized driver and inhibitor factor priorities, then assess the two directly elicited component propositions and the exploratory PEST summaries, display panel-composition sensitivity for all factors, and report method-specification, consistency, panel-composition, classification, and factor-inventory coverage checks.

4.1. Within-Set Priorities of Fandom Platform Factors

Table 7 reports factor priorities separately within the driver and inhibitor hierarchies. Each hierarchy is independently normalized to sum to 1.0. Weights and ranks are therefore interpreted only within the corresponding set; no cross-set magnitude comparison, combined 24-factor ranking, or substantive interpretation of the direct top-level item is used.

Table 7. Separate within-set priorities and ranks for the 12 drivers and 12 inhibitors.

Rank	Driver	Within-Driver Weight	Rank	Inhibitor	Within-Inhibitor Weight
1	D3 Convenient communication tools for artists	0.1862	1	H1 Rise in artists' fatigue level	0.1653
2	D1 Stable monetization	0.1806	2	H9 Excessive payment inducements	0.1581
3	D4 A way of collecting feedback from fandom	0.1549	3	H4 Artist privacy risks	0.1464
4	D2 Use as a promotion channel	0.1018	4	H3 Insufficient revenue sharing	0.1110
5	D9 Direct communication access for fandoms	0.0713	5	H2 Lack of support from the agency	0.0925
6	D5 A way of increasing revenue and diversifying the revenue model	0.0646	6	H11 Rise in fandoms' fatigue level	0.0712
7	D8 Enhanced ability to lock in and manage the fandom	0.0578	7	H6 Difficulty of attracting external artists	0.0543
8	D7 Acquisition of consumer data	0.0558	8	H12 Complexity of the platforms	0.0526
9	D10 Access to exclusive content	0.0480	9	H10 Backlash from the decline of the existing fandom communities	0.0497
10	D6 Ease of global expansion	0.0414	10	H5 High cost of building and operating platform	0.0437
11	D11 Integrated delivery of artist-related news and information	0.0204	11	H8 Lack of experience operating platforms	0.0336
12	D12 Provision of content translation	0.0172	12	H7 Consumer privacy risks	0.0217

Within the driver hierarchy, convenient communication tools for artists (D3; mean = 0.1862) and stable monetization (D1; 0.1806) have the two highest mean priorities, followed by collecting fandom feedback (D4; 0.1549). Within the inhibitor hierarchy, artist fatigue (H1; 0.1653), excessive payment inducements (H9; 0.1581), and artist privacy risks (H4; 0.1464) have the three highest mean priorities. D3 and H1 rank first in most CR-conditioned Monte Carlo draws, but panel-composition checks sometimes place D1 or H9 first. The results therefore support a small group of high-priority factors rather than an invariant first-place factor.

4.2. Assessment of Component Propositions and Exploratory PEST Summaries

The two coders agreed on 21 of the 24 primary PEST classifications (87.5%; unweighted Cohen's $\kappa = 0.829$, bootstrap 95% interval [0.622, 1.000]). Three disagreements were resolved using the pre-defined codebook and dominant-mechanism rule, yielding the consensus mapping in Table 5. Because PEST is not an elicited hierarchy, these reliability statistics assess reproducibility of the analyst-applied classification rather than agreement among respondents about macro-environmental priorities.

The component assessment supports both directly elicited propositions: artist-related conditions have the highest within-set component priority for drivers (Proposition 1) and inhibitors (Proposition 2), and the relevant component gaps remain positive under the evaluated respondent and firm-composition checks. The exploratory PEST summaries do not yield a comparably stable category hierarchy. On the driver side, Social leads the cumulative category sum while Economic leads the category-size-adjusted share; on the inhibitor side, Social leads under the reconciled mapping, while the identity and magnitude of the leading category are more classification-sensitive. These PEST patterns are therefore reported descriptively; no support verdict is assigned. Table 8 summarizes the proposition and exploratory PEST assessments; Table 9 reports the corresponding component priorities; and Table 10 reports the PEST category summaries.

Table 8. Summary of the primary component propositions and exploratory PEST assessments.

Analysis	Statement/Question	Assessment
Proposition 1	Artist-related conditions are the strongest driver component	Supported within the evaluated panel/hierarchy
Proposition 2	Artist-related conditions are the strongest inhibitor component	Supported within the evaluated panel/hierarchy
EQ1	How do driver priorities distribute across PEST categories?	No stable category dominance; aggregation- and panel-sensitive
EQ2	How do inhibitor priorities distribute across PEST categories?	No stable category dominance; classification- and panel-sensitive

Note: Proposition 1 and Proposition 2 concern directly elicited component priorities and are assessed for within-panel stability. EQ1 and EQ2 concern a secondary, non-elicited PEST classification; their assessments describe whether stable category dominance emerges across cumulative, category-size-adjusted, resampling, and classification checks; they do not constitute population tests.

Table 9. Component priorities within the separately normalized driver and inhibitor hierarchies. Values are means over 10,000 CR-conditioned simulations with 95% simulation intervals.

Factor Set	Component	Mean	95% Simulation Interval	P(Rank = 1)
Drivers	Artist	0.6235	[0.6193, 0.6275]	1.0000
Drivers	Entertainment Company	0.2196	[0.2155, 0.2235]	0.0000
Drivers	Fandom	0.1569	[0.1528, 0.1613]	0.0000
Inhibitors	Artist	0.5152	[0.5101, 0.5204]	1.0000
Inhibitors	Entertainment Company	0.1532	[0.1499, 0.1567]	0.0000
Inhibitors	Fandom	0.3316	[0.3263, 0.3369]	0.0000

Assessment of Proposition 1: Artist-related factors as the strongest driver.

Proposition 1 proposed that artist-related factors would be the strongest driver component. The artist component has a mean within-driver priority of 0.6235 (95% simulation interval [0.6193, 0.6275]), compared with 0.2196 for the company component and 0.1569 for the fandom component. The artist component ranks first in 100% of respondent and firm-cluster resamples; the artist-versus-strongest-competitor gap remains positive in both sensitivity intervals. Proposition 1 is supported.

Table 10. PEST category summaries. Category sums are reported alongside mean factor priorities and size-normalized shares; intervals are 95% CR-conditioned simulation intervals.

Factor Set	PEST Category	Category Sum (95% SI)	Mean Factor Priority	Size-Normalized Share (95% SI)
Drivers	Political	0.0558 [0.0543, 0.0573]	0.0558	0.1655 [0.1616, 0.1695]
Drivers	Economic	0.2452 [0.2417, 0.2486]	0.1226	0.3638 [0.3595, 0.3681]
Drivers	Social	0.3760 [0.3713, 0.3809]	0.0940	0.2789 [0.2747, 0.2833]
Drivers	Technological	0.3230 [0.3193, 0.3266]	0.0646	0.1917 [0.1892, 0.1942]
Inhibitors	Political	0.0217 [0.0210, 0.0224]	0.0217	0.0776 [0.0753, 0.0799]
Inhibitors	Economic	0.3670 [0.3632, 0.3707]	0.0917	0.3284 [0.3250, 0.3318]
Inhibitors	Social	0.4539 [0.4493, 0.4585]	0.1135	0.4062 [0.4016, 0.4107]
Inhibitors	Technological	0.1574 [0.1547, 0.1602]	0.0525	0.1879 [0.1847, 0.1911]

Assessment of EQ1: Exploratory driver PEST summary.

Social has the largest driver category sum (0.3760), ahead of Technological (0.3230), and the primary paired Social-versus-strongest-competitor gap is positive (0.0530; 95% simulation interval [0.0454, 0.0607]). However, Economic has the largest size-normalized share (0.3638), while Social falls to 0.2803 and its corresponding size-normalized gap is negative. The respondent-resampling and firm-cluster sensitivity intervals for the raw Social gap include zero. EQ1 therefore yields no stable PEST-category dominance across aggregation choices and plausible panel compositions.

Assessment of Proposition 2: Artist-related factors as the strongest inhibitor.

Proposition 2 proposed that artist-related conditions would be the strongest inhibitor component. The artist component has a mean within-inhibitor priority of 0.5152 (95% simulation interval [0.5101, 0.5204]), ahead of the fandom component (0.3316) and company component (0.1532). It ranks first in 98.13% of respondent-resampling samples and 97.98% of firm-cluster resamples; the gap over the strongest competitor remains positive in both 95% sensitivity intervals. Proposition 2 is supported within the evaluated panel and hierarchy.

Assessment of EQ2: Exploratory inhibitor PEST summary.

Under the reconciled mapping, Social has the largest inhibitor category sum (0.4539 versus 0.3670 for Economic) and also the largest size-normalized share. The Economic-versus-strongest-competitor gaps are negative in the primary simulation, while the respondent and firm-cluster sensitivity intervals do not establish a stable alternative dominance. Moreover, the identity of the largest unadjusted inhibitor category changes from Economic under the initial first-coder mapping to Social under the reconciled mapping. EQ2 therefore indicates classification-sensitive PEST summaries; the categories were not directly elicited as a preference hierarchy.

4.3. Distributional Analysis of Key Factors

Figures 3 and 4 display all 12 driver and all 12 inhibitor priorities with respondent-resampling and firm-cluster sensitivity intervals. These figures show panel-composition sensitivity beyond the narrower variation generated by repeated TFN sampling. For drivers, D3 and D1 have overlapping panel-resampling intervals, and both rank first under plausible panel compositions. For inhibitors, H1, H9, and H4 have overlapping panel-resampling intervals and remain close in rank. The full CR-conditioned simulation intervals and violin distributions are reported in Appendix B.

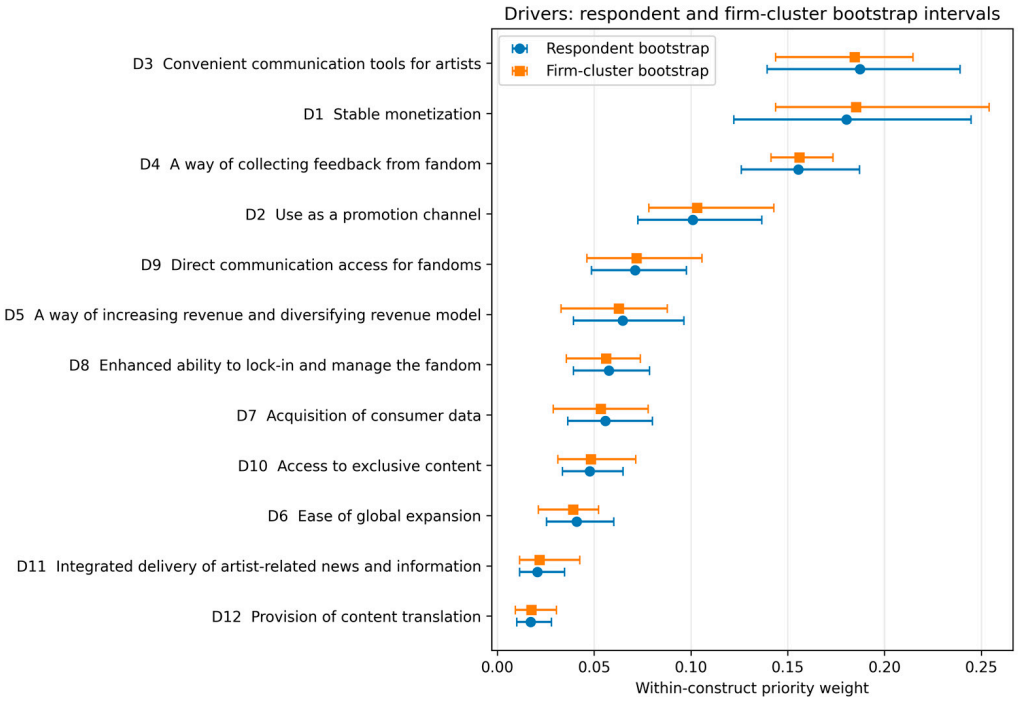


Figure 3. Driver priorities with 95% respondent-resampling and firm-cluster sensitivity intervals.

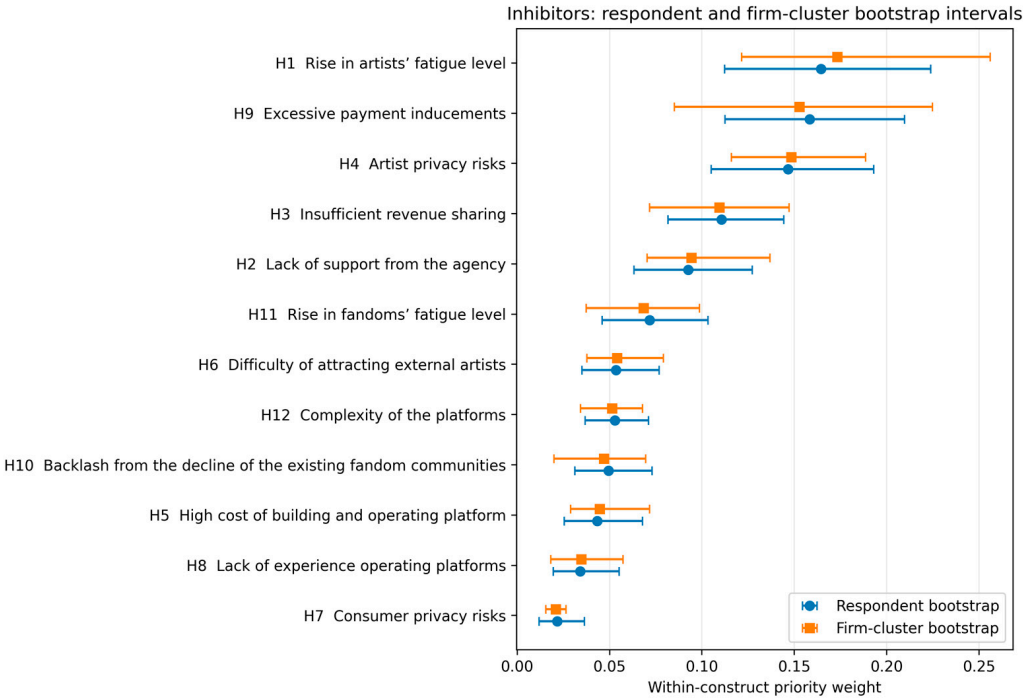


Figure 4. Inhibitor priorities with 95% respondent-resampling and firm-cluster sensitivity intervals.

4.4. Robustness of the Findings

The robustness analysis first addresses method specification. Using the original crisp Saaty judgments with AIP reproduces the primary driver ordering exactly (Spearman $\rho = 1.000$) and the inhibitor ordering almost exactly ($\rho = 0.993$); the Artist component remains first for both sets. Geometric-mean AIJ also retains Artist as the leading component, with rank correlations of 0.972 for drivers and 0.993 for inhibitors relative to the primary SF-AHP means [67]. At the factor level, AIJ keeps D3 first but moves D4 above D1, providing a concrete example of finer-grained specification variation. Replacing the primary TFN mapping with the published $d = 1$ and $d = 2$ alternatives [66] likewise leaves Artist first for

both sets. The d = 1 mapping reproduces the primary factor ordering for both hierarchies (ρ = 1.000 for drivers and inhibitors), whereas the more expansive d = 2 mapping yields ρ = 0.993 for drivers and 0.979 for inhibitors, with only adjacent lower-rank changes. Across the tested fuzzification and group-aggregation specifications, the component result remains stable, and factor rankings remain highly correlated; only some adjacent ranks change across specifications. Separately, an unconstrained TFN-draw diagnostic met CR < 0.10 for 88.1% of sampled expert–node matrices on average, supporting the use of explicit consistency conditioning in the stochastic specification.

Panel-composition analyses reinforce the component ordering while the leading factor within each set varies across scenarios. The Artist component ranks first in every firm-cluster resample for drivers and in 97.98% of cases for inhibitors. Excluding the largest firm cluster entirely, assigning equal weight to each firm, and all eight leave-one-firm-out scenarios also leave Artist first on both sides. However, the top driver changes from D3 to D1 when the largest cluster is excluded and under equal-firm weighting, and H9 becomes the top inhibitor in five of the eight leave-one-firm-out scenarios. These results are evidence of robustness within the observed eight-firm panel, not broader external robustness. The secondary PEST summaries remain more conditional: raw and size-adjusted aggregation point in different directions on the driver side, and classification choices change the leading unadjusted inhibitor category.

Factor-inventory coverage was assessed separately. The independent coverage review did not identify a material cross-cutting omission, while the source-traceability and corroboration checks identified specific areas of overlap or underrepresentation that inform interpretation of the fixed 24-factor inventory. Section 3.4 summarizes these checks, Section 5.3 discusses their implications, and Appendix A.2, Supplementary File S1, and the reproducibility package provide the detailed records.

5. Discussion and Conclusions

This study examined company experts' priorities within a broad organizational fandom-platform adoption decision in the South Korean entertainment industry using Stochastic Fuzzy AHP (SF-AHP). The analysis frames adoption as a coordination problem involving anticipated artist participation and burden, company viability and capability, and fandom access and experience. The discussion integrates the component, factor, exploratory PEST, method-specification, and factor-coverage findings around that organizational decision context.

5.1. Summary and Interpretation of Key Findings

Taken together, the results yield three main findings. First, within the separately normalized hierarchies and among the participating company experts, artist-related conditions receive the highest within-set component priority for both drivers and inhibitors, and this ordering persists under crisp AHP, alternative group aggregation, alternative TFN mappings, and the evaluated firm-composition checks. Second, factor-level results identify consistent leading tiers even as exact within-tier ranks vary: D3 and D1 remain the leading driver tier, while H1, H9, and H4 remain the leading inhibitor tier across plausible panel scenarios. Third, the secondary PEST analysis yields no stable macro-environmental hierarchy because cumulative, size-adjusted, panel-resampling, and classification assessments do not converge on a common category ordering.

The secondary PEST results provide a contextual view of the same factor priorities. Social has the largest driver category sum, but Economic leads after factor-count adjustment, and the respondent and firm-cluster raw-sum sensitivity intervals include zero. For inhibitors, Social has the largest category sum and size-normalized share under the reconciled

mapping, whereas the largest unadjusted category changes from Economic under the initial first-coder mapping to Social after reconciliation. The divergence across aggregation and classification choices indicates that no single macro-environmental category summarizes the pattern consistently.

The raw-versus-size-adjusted reversal also suggests different descriptive structures. Social-driver weight is distributed across several relational mechanisms—promotion (D2), fandom feedback (D4), direct communication access (D9), and exclusive content (D10)—whereas the Economic driver result is more concentrated around stable monetization (D1). These summaries distinguish weight distributed across several relational mechanisms from concentration around a smaller set of economic mechanisms. Because PEST classifies estimated factor priorities rather than forming an elicited hierarchy, the pattern is descriptive and does not test interactions among factors.

The directly elicited component results are clearer. The two component propositions are consistent with the modeled priority evidence: company experts assign the highest within-set priority to artist-related conditions in both hierarchies. Platform research makes such concentration theoretically plausible because contributor-side participation and output can exert asymmetric cross-side effects [5–7] and Korean platform research indicates that artist activity and coordinated company or platform support matter for channel performance [24]. This ordering should be expected most plausibly where the focal firm retains substantial coordination authority over platform access, monetization, data use, participation conditions, and support while simultaneously depending on sustained artist participation to generate cross-side attraction. The finding refines this literature by showing that, within the specified company-adoption decision, the stakeholder-level ordering is markedly more stable across panel and method specifications than the ordering of individual factors. This inference concerns company-side adoption priorities; whether artists or fandoms produce the same ordering is a separate empirical question.

These tensions are cross-side and involve power and appropriation as well as technical coordination. Communication access can increase fan-facing value while intensifying artist workload and privacy exposure; monetization can support company viability while increasing fan payment pressure or distributional conflict; and data and lock in capabilities can improve organizational coordination while increasing consumer-governance concerns. The same platform feature may therefore create value for the focal firm while shifting relational labor, privacy risk, payment pressure, or other burdens to another side. Because the evidence comes from company professionals, these cross-side effects are theoretical interpretations of how governance burdens may be distributed rather than measured artist- or fandom-side outcomes [9–15,19,26]. They motivate direct stakeholder-side research on how workload, privacy, payment pressure, and control are experienced.

At the individual-factor level, the results identify consistent leading tiers rather than a single invariant rank order. D3 and D1 exchange first place under plausible panel-composition scenarios, while H1, H9, and H4 remain close and H9 leads in several leave-one-firm-out analyses. The contrast between robust component ordering and rank variation among leading factors is consistent with a hierarchical representation in which a broad stakeholder location can remain stable while specific mechanisms exchange rank. Component priorities were elicited directly, whereas global factor priorities combine component and within-component judgments, providing an alternative design-based explanation for this contrast. Alternative elicitation structures are therefore needed to test whether the same pattern reflects managers' cognitive organization of the decision.

5.2. Theoretical and Practical Implications

From a theoretical perspective, the study adds to organizational-adoption research in an agency-mediated, multi-sided fandom-platform setting while keeping the roles of the underlying theories distinct. Multi-sided platform theory explains why cross-side dependence and asymmetric contributor effects make an artist-related coordination focus plausible [3–7]; organizational-adoption research locates that assessment in the focal firm rather than in users [48–50]; and dual-factor theory justifies keeping enabling and inhibiting beliefs separate [27,28]. Service-dominant logic and value-capture theory help interpret why the same coordination arrangement may generate benefits and burdens across different sides [9–15,35–37]. Against that background, the component-versus-factor result refines organizational-adoption thinking: company experts show robust stakeholder-level priority while the precise leading mechanism can vary among close alternatives. This pattern is most applicable to agency-mediated arrangements in which firms coordinate platform access, monetization, data, and participation conditions while depending on sustained creator participation. Relative to prior research, the result is consistent with fandom-platform and creator-economy studies that emphasize artist participation, relational labor, support, monetization, and contributor-side dependence [5,19,24–26,68–70]; it extends organizational-adoption work by showing how a focal firm's evaluative attention can be distributed across stakeholder-related condition blocks in a multi-sided setting [48–50], and it makes visible the coordination-versus-appropriation tensions emphasized in platform-governance and value-capture research [9–15]. The contribution is a firm-level priority structure that links these mechanisms across stakeholder-related condition blocks and shows how organizational attention can remain concentrated on one ecosystem side even when the leading mechanism within that side varies.

From a practical perspective, the findings identify decision tensions and candidate governance responses for evaluation.

Although the focal decision-maker is the entertainment company, artist- and fandom-related implications are included as cross-side governance considerations that enter company-side adoption judgments. The evidence directly supports the relative priority of the evaluated conditions. Specific design or governance actions are therefore presented as candidate responses informed by the observed priorities and prior research, not as interventions evaluated in this study.

- For Platform Developers: the priority pattern suggests that communication and service features should be evaluated not only for engagement benefits but also for the operating and relational burdens they can create. Message management, privacy controls, translation, moderation, and usability are plausible governance levers discussed in related fandom-platform and creator research [19,22,24–26].
- For Entertainment Companies: convenient communication and stable monetization form the leading driver tier, while artist fatigue, payment pressure, and artist privacy form the leading inhibitor tier. This combination identifies a coordination tension, not a prescription to maximize any one feature. Candidate responses for future evaluation include preserving artist discretion over interaction frequency, using asynchronous formats where appropriate, bounding synchronous sessions, strengthening moderation and privacy safeguards, reviewing compensation and payment design, and monitoring engagement together with workload and governance indicators. These possibilities are motivated by the observed priorities and prior literature [19,68–70].
- For Artist-Related Governance: the company-expert results place artist communication benefits alongside workload, support, compensation, and privacy concerns. Related research on relational labor, streaming-era compensation, platform strategy, visibility, and allocation rules [19,24,26,68–72] suggests that participation arrangements may

need explicit support, moderation, privacy protection, and transparent compensation terms. Because artist priorities were not directly elicited, direct artist-side elicitation and contractual research are needed before converting these considerations into stakeholder-specific recommendations.

- For Fandom-Related Governance: the company-expert priorities place access, exclusivity, and translation alongside payment pressure, privacy, usability, and community displacement. Transparent pricing, meaningful data controls, accessible interfaces, and mechanisms for community continuity and feedback are candidate governance responses for direct future evaluation. Future studies should test these responses with fandom participants and observed platform outcomes.

5.3. Limitations and Future Research

This study has several limitations, each pointing to future work. First, external validity has three distinct boundaries. Statistically, the 28 respondents from eight firms were recruited non-probabilistically and cannot support population generalization to the Korean entertainment industry, artists, or fandoms. Analytically, any transferability is most plausible in creator settings that share similar agency-mediated coordination, creator dependence, monetization, and platform-governance structures. Contextually, the South Korean entertainment industry combines a distinctive artist-management system, intensive fandom culture, a global expansion model, and a concentrated fandom-platform environment; these institutional features may themselves help explain the high priority assigned to artist-related conditions. Bootstrap or resampling stability within the eight-firm panel does not establish external robustness. Replication across countries, platform types, ownership structures, artists, and fandoms is required.

Second, the panel is concentrated: Firms A and B account for 16 of the 28 completed respondents, and the three largest firms account for 20. Firm-resampling, equal-firm weighting, largest-firm exclusion, and leave-one-firm-out analyses assess sensitivity to this observed concentration but cannot create expertise diversity that was not sampled. Recruitment established decision-relevant occupational eligibility, while detailed respondent-level professional profiles were not retained in the analytical AHP response dataset. Available recruitment-stage information supports aggregate functional-area reporting for 19 respondents and industry-experience reporting for 26; responsibility level was not retained in a form suitable for reliable aggregate reporting, topic familiarity was not measured on a standardized respondent-level scale, and direct involvement in specific adoption or operation episodes was not separately measured. This limits fine-grained comparison of expertise within the panel even though occupational eligibility was established for all included respondents. Future expert panels should collect pre-specified categorical expertise indicators under privacy-preserving protocols that permit complete aggregate reporting.

Third, the results depend on the specified set of 24 factors and the pre-specified Artist–Company–Fandom hierarchy. The factor-development process was broad and iterative rather than a prospectively logged systematic review. Source-traceability, corroboration, and independent coverage checks strengthen the evidentiary basis for the inventory and identify specific areas of overlap or underrepresentation, but they do not establish exhaustive content validity. Future factor development should test these boundaries prospectively across additional sources and stakeholder groups.

Fourth, standard AHP represents the decision through a comparatively decomposable hierarchy, while a multi-sided platform is characterized by reciprocal dependencies, feedback loops, and complementarities. AHP remains useful here because the study's purpose is to elicit relative priorities within a pre-specified decision structure, and component weights were compared directly and not inferred solely from factor sums. It does not,

however, model feedback between artist, company, and fandom conditions. The observed component-versus-factor pattern may also partly reflect the direct elicitation of components and hierarchical synthesis of factor priorities. Future work could use the Analytic Network Process, configurational methods, or mixed qualitative–quantitative designs to model interdependence explicitly.

Fifth, the survey captured a cross-sectional snapshot and used a broad adoption frame without separating proprietary platform development, participation in an existing platform, and continued operation. Some factors—such as development cost, operating capability, external-artist acquisition, communication access, and translation—may have different relevance across these modes or over the platform life cycle. In addition, the real-time CR requirement may have suppressed genuine ambiguity by prompting respondents to adjust judgments until the threshold was met. The export preserves completion patterns and final observed judgments but not warning counts, CR values before respondent adjustment, or matrix-level judgment-adjustment histories, and the reasons the two incomplete participants discontinued were not recorded. Future studies should preserve process logs and compare priority structures across distinct adoption modes and time periods.

Sixth, PEST is a secondary, non-elicited classification, not a directly elicited AHP level. Categories contain unequal numbers of factors; Political contains only one factor in each hierarchy, and several factors plausibly span multiple mechanisms. Concrete coding choices illustrate this sensitivity. Artist privacy risks (H4), for example, were initially coded Political but reconciled as Social under the dominant-mechanism rule because H4 was treated primarily as a relational-boundary concern; this reassignment changes the leading unadjusted inhibitor category from Economic under the initial mapping to Social under the reconciled mapping. Related constructs can also receive different codes when their dominant mechanisms differ: artist fatigue (H1) is classified as Social whereas fandom fatigue (H11) is classified as Technological, and the coding of artist privacy risks (H4) differs from that of consumer privacy risks (H7), which is classified as Political. Size-normalized summaries and independent coding improve transparency but remain analyst-created diagnostics, not respondent preferences. These examples demonstrate the classification sensitivity of PEST totals; the category preferences themselves were not directly elicited. PEST is therefore used only for exploratory description; cross-national and multi-coder replications should test whether independently generated mappings yield similar patterns.

Seventh, the factor set includes payment pressure, data, privacy, community displacement, artist fatigue, compensation, and support, but the study ranks company experts' perceived relevance of these conditions; it does not directly measure how artists and fandoms experience power, control, dependency, value appropriation, or relational labor. Managerial respondents may interpret costs differently from the stakeholders who bear them. Qualitative, contractual, critical, and stakeholder-panel research is needed to examine these trade-offs directly and to evaluate the governance responses proposed in Section 5.2.

5.4. Conclusions

The rise of fandom platforms reflects a broader shift toward direct artist–fan interaction, but the company-level organizational adoption decision is not reducible to launching a communication feature. Within the specified factor set and hierarchy, company experts place the greatest within-set priority on artist-related conditions among both drivers and inhibitors, and this component ordering persists across crisp AHP, alternative group aggregation, alternative TFN mappings, and multiple panel-composition checks. At the factor level, convenient communication tools for artists (D3) and stable monetization (D1) form the leading driver tier, while artist fatigue (H1), excessive payment inducements (H9), and artist privacy risks (H4) form the leading inhibitor tier; these leading sets remain

consistent even though close alternatives exchange rank across several panel-composition checks. This pattern indicates that a robust stakeholder-level coordination focus can coexist with rank variation among closely competing mechanisms. The secondary PEST analysis remains descriptive and classification-sensitive and does not constitute an elicited macro-environmental hierarchy. These conclusions are grounded in the evaluated factors, broad adoption frame, eight-firm expert panel, and South Korean institutional setting; extending them to stakeholder preferences, causal effects, or population-level patterns requires separate evidence.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jtaer21080285/s1, Supplementary Literature Audit and Inventory-Coverage Assessment (including source traceability, the independent coverage and concept-domain omission review, PEST-classification reliability and reconciliation, and PEST mapping-sensitivity analysis).

Author Contributions: Conceptualization, J.J.K. and S.-G.L.; methodology, J.J.K.; software, J.J.K.; validation, J.J.K.; formal analysis, J.J.K.; investigation, J.J.K.; data curation, J.J.K.; writing—original draft preparation, J.J.K. and S.Y.L.; writing—review and editing, J.J.K. and S.-G.L.; visualization, J.J.K.; supervision, S.-G.L.; project administration, J.J.K. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Prior IRB review for the anonymous expert survey was not required under Article 13(1)(2) of the Enforcement Rule of the Bioethics and Safety Act of the Republic of Korea. The survey was a minimal-risk online elicitation involving adult professionals. No names, telephone numbers, email addresses, or other direct personal identifiers were collected through the questionnaire or included in the analytical dataset. Company and role eligibility were checked during recruitment; actual company names and detailed job information were not retained in the analytical dataset. An anonymized firm code was retained solely for aggregate sample description and firm-composition sensitivity analyses and is reported as Firm A through Firm H. No sensitive personal information as defined in Article 23 of the Personal Information Protection Act of the Republic of Korea was collected or recorded in the survey dataset.

Informed Consent Statement: Electronic informed consent was obtained from all 28 survey participants. Before accessing the survey, participants received information concerning the study purpose, procedures, expected completion time, voluntary participation, and the use and confidential handling of the data for academic research and manuscript preparation. Voluntary completion and submission of the survey constituted consent to participate.

Data Availability Statement: The version 1.1.0 confidentiality-safe public repository available on Zenodo at https://doi.org/10.5281/zenodo.21990853 contains the integrated SF-AHP analysis notebook, factor definitions, independent and reconciled PEST-coding records, exact primary and alternative crisp-to-TFN mappings, crisp AHP-AIP and geometric-mean AIJ robustness code and aggregate outputs, alternative-fuzzification outputs, aggregate panel-profile and panel-composition artifacts, Supplementary File S1, and the blank participant information and consent notice. Participant-level pairwise judgments, respondent-specific diagnostic files, the respondent-to-firm linkage, and linkage-derived intermediate arrays are not publicly deposited because their combination with high-precision firm-composition results could increase indirect re-identification risk in the small expert panel. Restricted verification materials required for participant-level or firm-linkage-dependent re-estimation may be considered for the handling editor or qualified researchers upon a justified request, through secure transfer and subject to appropriate confidentiality, data-use, and applicable institutional requirements.

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and language editing. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1. Definitions of Drivers and Inhibitors

Table A1. Definitions of drivers and inhibitors.

Drivers and Inhibitors		Definitions
Drivers		
D1	Stable monetization	Obtain relatively predictable and recurring income streams—primarily through paid subscriptions—that reduce revenue volatility and provide financial continuity for artists, including during periods of limited promotional activity.
D2	Use as a promotion channel	Expand the fandom base by utilizing the platform as a promotion channel
D3	Convenient communication tools for artists	Provide user-friendly and efficient technological tools that reduce the operational burden on artists when interacting with fans (e.g., ease of posting, message management, and platform usability)
D4	A way of collecting feedback from fandom	Use it as a channel to receive direct feedback on the fandom's needs and activities related to the artist's activities
D5	A way of increasing revenue and diversifying the revenue model	Expansion of income sources using artists, such as subscription sales and MD sales, thus securing profits through activities on the platform even during the artists' inactive period
D6	Ease of global expansion	Take advantage of online services to target overseas markets through an app-type platform
D7	Acquisition of consumer data	Obtain customer data and use it for various purposes such as content and product recommendations, service provision, etc.
D8	Enhanced ability to lock in and manage the fandom	Manage fandom consistently and systematically across multiple channels and platforms
D9	Direct communication access for fandoms	Enable fans to directly communicate with artists and experience social closeness and immediacy through the platform
D10	Access to exclusive content	Provide exclusive content that cannot be found on other platforms
D11	Integrated delivery of artist-related news and information	Whenever there is new content, it can be checked through push notifications
D12	Provision of content translation	Improve accessibility/usability by translating the content
Inhibitors		
H1	Rise in artists' fatigue level	Communication through the fandom platform can be perceived as an additional task for artists in addition to existing activities, increasing artists' fatigue
H2	Lack of support from the agency	Difficult for artists to participate on the platform continuously due to the lack of support from the agency
H3	Insufficient revenue sharing	Low revenue distribution for artists in the entire ecosystem (estimated at 10–15% of total sales)
H4	Artist privacy risks	Risk of privacy controversies such as exposure of private life (romance rumor, cigarettes, etc.) in unmanageable situations such as live broadcasting
H5	High cost of building and operating platform	High cost of initial platform development and difficult to secure profitability through platform operation (burden of operating costs)
H6	Difficulty of attracting external artists	Difficult to obtain external artists, and only financial incentives can be used

Table A1. *Cont.*

Drivers and Inhibitors		Definitions
H7	Consumer privacy risks	Utilization of user data with respect to privacy issues
H8	Lack of experience operating platforms	Sense of difference due to inexperience in worldview building and storytelling in content planning
H9	Excessive payment inducements	Discomfort that the fandom platform is not for the convenience of fan activities, but for the formation of a profit structure for entertainment companies
H10	Backlash from the decline of the existing fandom communities	Decline of the existing spontaneously operating fandom community due to the platform's monopoly position
H11	Rise in fandoms' fatigue level	Fandom's fatigue level rises since the fandom platform offers continuous experiences while traditional communities offer fragmented and limited time experiences
H12	Complexity of the platforms	Consumers' maladaptation to new services (perceived as an unfamiliar concept)

Note on H3: The 10–15% parenthetical is reproduced verbatim because it formed part of the original survey instrument presented to respondents. It is retained to preserve fidelity to the pre-specified operational definition and is not presented as a universal or current industry benchmark. The cited literature supports revenue-sharing design and artist-compensation concerns at the construct level rather than validating a uniform percentage across platforms and contracts [5,19,69,70].

Appendix A.2. Factor Identification and Consolidation Protocol

The set of 24 factors was finalized before data collection through a broad, iterative, multi-channel process. The source pool included academic work on fandom platforms, the fan economy, creator and community platforms, and organizational technology adoption, together with Korean government-affiliated reports, industry materials, and press coverage of leading platforms. Academic literature was searched primarily through Google Scholar for broad discovery. Comparable combinations of the principal keywords were also searched in Scopus and Web of Science to identify additional academic studies and to consult associated citation, indexing, and journal information, and in the Korea Citation Index to strengthen coverage of Korean-language and Korea-context research. Google web searches were used primarily to locate government-affiliated reports, industry materials, and other non-academic sources. Search terms included combinations of "fandom platform," "fan platform," "K-pop platform," "Weverse," "Bubble," "creator economy," "fan economy," "platform monetization," and "multi-sided platform." Citation, indexing, and journal information served as supplementary source-appraisal information rather than as mechanical inclusion or exclusion criteria. Available pre-survey provenance records contain 11 source records, one recoverable only at the issue level; because the development process was not prospectively logged as a PRISMA-style review, these records are not interpreted as a complete screening count or bounded search period. The process was organized around the three stakeholder-related condition blocks and the distinction between conditions expected to encourage and conditions expected to constrain company-level adoption.

Complete database-result counts, date-bounded search logs, candidate-factor exclusions, records identifying the database through which each source was first discovered, and item-level screening decisions from the factor-development stage were not retained. To strengthen source traceability for factors with less complete pre-survey documentation, a factor-focused corroboration audit was conducted on 26 July 2026 using English- and Korean-language search concepts across official publisher pages, institutional research portals, the Korea Citation Index, and accessible full text located through web search. The audit focused on H2, H3, H4, and H8 and recorded 48 factor-level screening events: 22 included screening decisions and 26 exclusions, yielding 18 unique included publications and 23 final factor–source mappings. Search-engine total-result estimates were not treated

as screened records. The audit verified Korean-language and Korean-market sources, documented factor-specific inclusion and exclusion logic, and added corroborating literature where pre-survey documentation was weaker. Records supporting substantively different constructs were not used as corroboration for a frozen factor; relevant divergent concepts were instead carried into the concept-domain omission analysis. The corroboration audit is reported separately from the pre-survey factor-development record so that the timing and evidentiary role of each source are transparent.

Supplementary File S1 reports the pre-survey provenance record, the 24-factor source crosswalk and registry, the factor-focused H2/H3/H4/H8 corroboration audit, the independent coverage and concept-domain omission review, the PEST-classification reliability and reconciliation record, and the PEST mapping-sensitivity reanalysis. Pre-survey sources and later corroborating sources are distinguished throughout. The elicited factor inventory and stakeholder-related component assignments remained unchanged; independent classification and reconciliation were used only for the secondary exploratory PEST mapping.

Appendix B

Appendix B.1. CR-Conditioned Simulation Intervals for All Driver and Inhibitor Factors

Figure A1 presents the CR-conditioned simulation intervals for all driver and inhibitor factors.

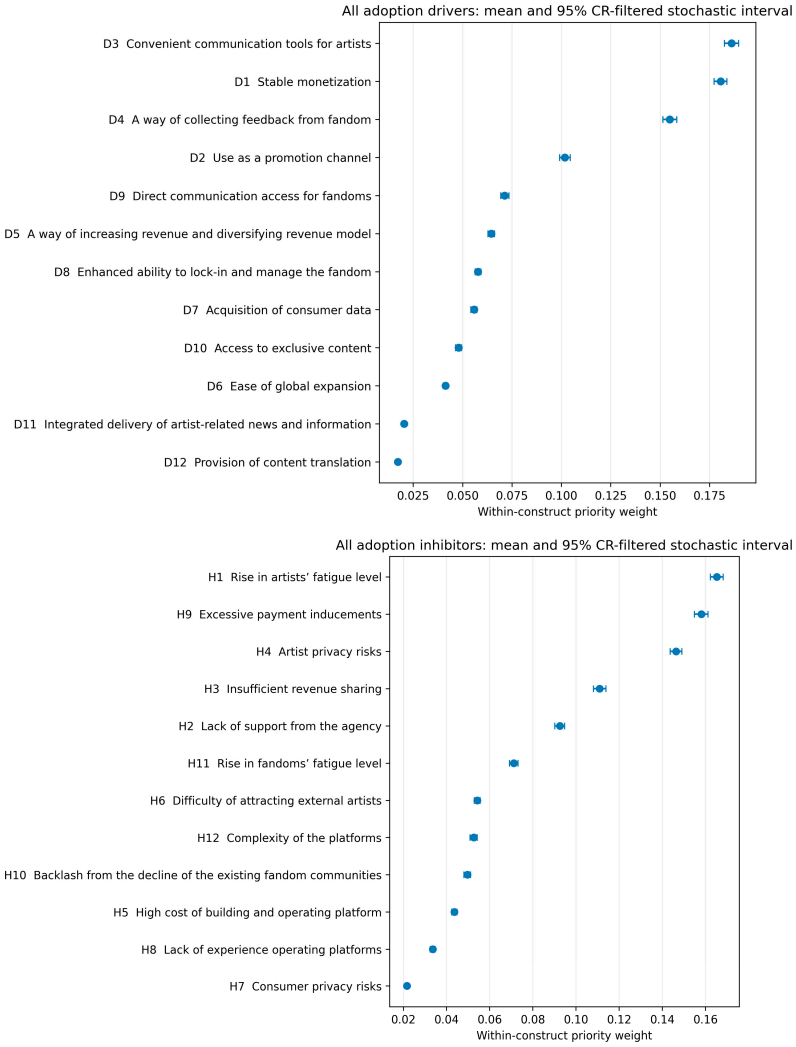


Figure A1. Mean within-set priorities and 95% CR-conditioned simulation intervals for all 12 drivers and all 12 inhibitors.

Appendix B.2. CR-Conditioned Stochastic Distributions for All Driver and Inhibitor Factors

Figure A2 presents the corresponding CR-conditioned stochastic distributions.

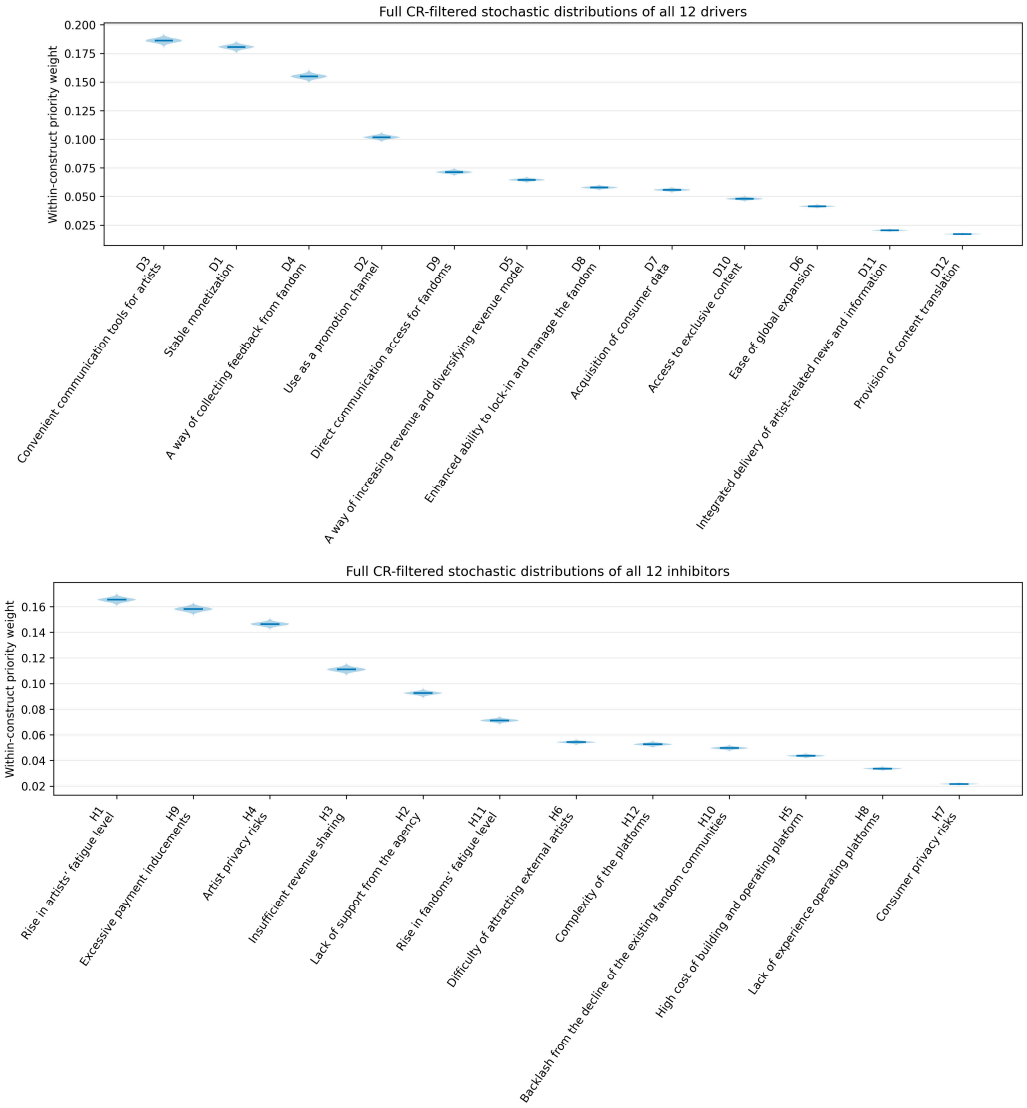


Figure A2. Violin distributions of within-set priorities over 10,000 CR-conditioned SF-AHP iterations.

Appendix C

Appendix C.1. Robustness Procedures—Classification Protocol and Sensitivity

The Artist–Company–Fandom assignments were fixed before the pairwise-comparison survey and defined the elicited AHP branches; they were therefore not targets of independent classification. PEST is a secondary analytical overlay and is the only mapping subjected to independent classification. The second coder used the original factor labels and definitions, a common PEST codebook, and balanced factor-independent examples in 'Codebook Orientation and Generic Practice.' The coder did not see the manuscript, original PEST assignments, propositions, weights, rankings, or analytical results. Each factor was classified according to its direct and dominant substantive mechanism rather than possible downstream commercial consequences, and all 24 items were completed before any study item was discussed with the research team. Pre-discussion percentage agreement and Cohen's kappa were calculated for PEST classification, followed by a transparent disagreement and reconciliation record. All PEST summaries use the consensus classification.

Appendix C.2. Panel-Composition Robustness Procedures

Panel-composition robustness is reported separately for component priorities, leading-factor rank-one probabilities, deterministic panel scenarios, leave-one-firm-out results, and exploratory PEST category gaps (Tables A2–A6). Percentile intervals are used as resampling sensitivity summaries rather than population-inferential confidence intervals.

Table A2. Panel-composition robustness of component priorities. Values are resampling means with 95% percentile sensitivity intervals over 10,000 replicates.

Component	Respondent Resampling	Firm-Cluster Resampling
Artist (drivers)	0.6241 [0.5429, 0.6952]	0.6291 [0.5639, 0.7032]
Company (drivers)	0.2191 [0.1601, 0.2884]	0.2115 [0.1228, 0.2857]
Fandom (drivers)	0.1567 [0.1126, 0.2134]	0.1594 [0.1025, 0.2418]
Artist (inhibitors)	0.5144 [0.4225, 0.6054]	0.5255 [0.4418, 0.6429]
Company (inhibitors)	0.1529 [0.1012, 0.2223]	0.1546 [0.1063, 0.2083]
Fandom (inhibitors)	0.3327 [0.2448, 0.4226]	0.3198 [0.1887, 0.4381]

Table A3. Leading individual-factor rank-one probabilities under respondent and firm-cluster resampling.

Factor	Respondent Resampling	Firm-Cluster Resampling
D3 Convenient communication tools for artists	0.5434	0.5703
D1 Stable monetization	0.4420	0.4285
H1 Rise in artists' fatigue level	0.4330	0.5182
H9 Excessive payment inducements	0.3772	0.4053

Table A4. Deterministic panel-composition sensitivity scenarios. Values in parentheses are mean priorities.

Outcome	Largest Firm Cluster Excluded	Equal Firm Weighting
Top driver	D1 (0.2038)	D1 (0.2024)
Top inhibitor	H1 (0.2069)	H1 (0.2110)

Table A5. Leave-one-firm-out sensitivity. Priorities are deterministic means after omitting the indicated firm cluster.

Omitted Firm Cluster	Top Driver	Top Inhibitor	Artist Component Rank (Driver/Inhibitor)
Largest firm (n = 10; Table 6 Firm A)	D1 (0.2038)	H1 (0.2069)	1st/1st
Second-largest firm (n = 6; Table 6 Firm B)	D3 (0.1789)	H9 (0.1703)	1st/1st
Four-person firm (n = 4; Table 6 Firm C)	D1 (0.1893)	H9 (0.1766)	1st/1st
Two-person firm 1	D3 (0.1910)	H1 (0.1718)	1st/1st
Two-person firm 2	D3 (0.1931)	H9 (0.1673)	1st/1st
Two-person firm 3	D3 (0.1897)	H9 (0.1634)	1st/1st
One-person firm 1	D3 (0.1925)	H1 (0.1656)	1st/1st
One-person firm 2	D1 (0.1852)	H9 (0.1596)	1st/1st

Note: The artist component ranked first in both hierarchies in all eight leave-one-firm-out scenarios. The separately held restricted linkage addendum uses cluster-size-based robustness labels rather than company identities; equal-sized clusters are distinguished numerically.

Table A6. Exploratory PEST category-gap sensitivity under respondent and firm-cluster resampling. Gaps compare the focal descriptive category with its strongest competitor.

Exploratory Contrast/Measure	Respondent-Resampling Mean Gap [95% Interval]	Firm-Cluster Mean Gap [95% Sensitivity Interval]	Interpretation
EQ1/category sum	+0.0481 [−0.0125, 0.1072]	+0.0568 [−0.0005, 0.1428]	No stable dominance
EQ1/size-normalized share	−0.0835 [−0.2080, 0.0438]	−0.0851 [−0.2044, 0.0360]	No stable dominance
EQ2/category sum	−0.0873 [−0.1986, 0.0203]	−0.1016 [−0.2520, 0.0250]	No stable dominance
EQ2/size-normalized share	−0.0785 [−0.1801, 0.0178]	−0.0917 [−0.2305, 0.0223]	No stable dominance

Appendix C.3. Consistency-Conditioned Simulation and Alternative Expert-Weight Sensitivity

The primary simulation retains only sampled matrices with CR < 0.10. Table A7 shows that alternative Beta-weight specifications leave the main factor-rank patterns and component conclusions essentially unchanged while changing interval width. Additional method-specification checks reported in Section 4.4 and the public repository compare crisp AHP-AIP, geometric-mean AIJ, and two alternative TFN mappings; all retain Artist as the leading component in both hierarchies, while some adjacent factor ranks change. Table A8 reports the final observed consistency ratios by matrix; these values reflect the survey's real-time consistency enforcement and are not interpreted as unconstrained expert inconsistency measures.

Table A7. Sensitivity to alternative expert-weight distributions.

Weight Specification	Driver Rank Corr.	Inhibitor Rank Corr.	Mean Interval Width	P(Artist First, Drivers)	P(Artist First, Inhibitors)	EQ1	EQ2
Equal	1.000	1.000	0.0039	1.0000	1.0000	NSD	NSD
Beta(1,1)	1.000	1.000	0.0331	1.0000	0.9996	NSD	NSD
Beta(2,1)	1.000	1.000	0.0205	1.0000	1.0000	NSD	NSD
Beta(5,1)	1.000	1.000	0.0105	1.0000	1.0000	NSD	NSD
Beta(8,1)	1.000	1.000	0.0075	1.0000	1.0000	NSD	NSD

Note: NSD = No Stable Dominance. Alternative expert-weight specifications preserve the primary component conclusions. EQ1 and EQ2 are exploratory PEST summaries; no proposition verdict is assigned.

Table A8. Observed consistency ratios by elicited matrix.

Node	Matrix Order	N	Mean CR	Median CR	95th Percentile	Maximum CR
DRU	3	28	0.0449	0.0516	0.0876	0.09040
D_A	4	28	0.0615	0.0693	0.0933	0.09999
D_C	4	28	0.0648	0.0754	0.0972	0.09951
D_F	4	28	0.0701	0.0813	0.0946	0.09698
INU	3	28	0.0423	0.0516	0.0904	0.09609
I_A	4	28	0.0584	0.0685	0.0968	0.09888
I_C	4	28	0.0660	0.0759	0.0988	0.09997
I_F	4	28	0.0587	0.0626	0.0976	0.09853

Note: Saaty's Random Index (RI) values are 0.58 for order-3 matrices and 0.90 for order-4 matrices.

Appendix C.4. Robustness Procedures—Aggregation and Method Specification

Group importance is computed differently for the two analytical lenses. The three stakeholder-related components are directly elicited within separate driver and inhibitor hierarchies; their priorities are therefore compared within the corresponding set. The primary group aggregation uses equal-weight aggregation of individual priorities (AIP). Method-specification sensitivity additionally uses the original crisp Saaty judgments under AIP, a geometric-mean aggregation-of-individual-judgments (AIJ) specification [67], and

two alternative published TFN mappings [66]. PEST is a secondary non-elicited classification and is summarized from the estimated factor priorities rather than treated as a second AHP parent.

Table A9. Primary and alternative crisp-to-TFN mappings used in the robustness analyses.

Crisp Value	Primary Mapping	d = 1 Mapping [66]	d = 2 Mapping [66]
1	(1, 1, 1)	(1, 1, 2)	(1, 1, 3)
2	(1, 2, 3)	(1, 2, 4)	(1, 2, 4)
3	(2, 3, 4)	(2, 3, 4)	(1, 3, 5)
4	(3, 4, 5)	(2, 4, 6)	(2, 4, 6)
5	(4, 5, 6)	(4, 5, 6)	(3, 5, 7)
6	(5, 6, 7)	(4, 6, 8)	(4, 6, 8)
7	(6, 7, 8)	(6, 7, 8)	(5, 7, 9)
8	(7, 8, 9)	(6, 8, 9)	(6, 8, 9)
9	(8, 9, 9)	(8, 9, 9)	(7, 9, 9)

Note: Reciprocal judgments use $(l, m, u)^{-1} = (1/u, 1/m, 1/l)$. The d = 1 and d = 2 columns reproduce the alternative scale specifications used in the robustness analysis.

References

1. Rochet, J.-C.; Tirole, J. Platform Competition in Two-Sided Markets. *J. Eur. Econ. Assoc.* **2003**, *1*, 990–1029. [CrossRef]
2. Van Alstyne, M.W.; Parker, G.G.; Choudary, S.P. Pipelines, Platforms, and the New Rules of Strategy. *Harv. Bus. Rev.* **2016**, *94*, 54–62.
3. Adner, R. Ecosystem as Structure: An Actionable Construct for Strategy. *J. Manag.* **2017**, *43*, 39–58. [CrossRef]
4. Jacobides, M.G.; Cennamo, C.; Gawer, A. Towards a Theory of Ecosystems. *Strateg. Manag. J.* **2018**, *39*, 2255–2276. [CrossRef]
5. Bhargava, H.K. The Creator Economy: Managing Ecosystem Supply, Revenue Sharing, and Platform Design. *Manag. Sci.* **2022**, *68*, 5233–5251. [CrossRef]
6. Zhang, K.; Evgeniou, T.; Padmanabhan, V.; Richard, E. Content Contributor Management and Network Effects in a UGC Environment. *Mark. Sci.* **2012**, *31*, 433–447. [CrossRef]
7. Chu, J.; Manchanda, P. Quantifying Cross and Direct Network Effects in Online Consumer-to-Consumer Platforms. *Mark. Sci.* **2016**, *35*, 870–893. [CrossRef]
8. Sutherland, M. The Power of BTS and K-Pop, the Problem with Streaming's 20% Growth, and Other Notes from IFPI's Global Music Report. Available online: https://variety.com/2021/music/news/bts-streaming-nearly-20-growth-and-other-takeaways-from-the-ifpi-global-report-1234936526/ (accessed on 19 June 2026).
9. Teece, D.J. Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy. *Res. Policy* **1986**, *15*, 285–305. [CrossRef]
10. Brandenburger, A.M.; Stuart, H.W. Value-based Business Strategy. *J. Econ. Manag. Strategy* **1996**, *5*, 5–24. [CrossRef]
11. Priem, R.L. A Consumer Perspective on Value Creation. *Acad. Manag. Rev.* **2007**, *32*, 219–235. [CrossRef]
12. Lepak, D.P.; Smith, K.G.; Taylor, M.S. Value Creation and Value Capture: A Multilevel Perspective. *Acad. Manag. Rev.* **2007**, *32*, 180–194. [CrossRef]
13. Dai, G.; Zhang, L.; Zhang, Q.; Mao, M. Navigating Tensions Between Value Creation and Capture in Ecosystems. *J. Bus. Res.* **2024**, *170*, 114333. [CrossRef]
14. Helfat, C.E.; Raubitschek, R.S. Dynamic and Integrative Capabilities for Profiting from Innovation in Digital Platform-Based Ecosystems. *Res. Policy* **2018**, *47*, 1391–1399. [CrossRef]
15. Huber, T.L.; Kude, T.; Dibbern, J. Governance Practices in Platform Ecosystems: Navigating Tensions Between Cocreated Value and Governance Costs. *Inf. Syst. Res.* **2017**, *28*, 563–584. [CrossRef]
16. Shin, C.-H.; Hwang, S.-J. The Case Study of the Weverse as Global Fandom Platform. *e-Bus. Stud.* **2022**, *23*, 23–39. [CrossRef]
17. Lee, J.M.; Lau, G. Uniting Global Fans and Revolutionizing K-Pop Marketing: Weverse, a Global Fan Community Platform. *Asia Pac. Bus. Rev.* **2026**, *32*, 595–617. [CrossRef]
18. Song, M. A Study on the Business Model of a Fan Community Platform 'Weverse'. *Int. J. Adv. Smart Converg.* **2021**, *10*, 172–182. [CrossRef]
19. Lee, S.; Prey, R. The Labor Process of Relational Labor: The Case of the K-Pop Fan Platform "Bubble". *Pop. Music Soc.* **2025**, *48*, 416–436. [CrossRef]

20. Hong, S.Y.; Kim, S.I. A Study on User Experience Design of Fandom Platform Applications in the Media Entertainment Industry: Focused on Weverse and Universe. *J. Digit. Art Eng. Multimed.* **2022**, *9*, 451–460. [CrossRef]
21. Kim, H.-S.; Kwak, N.-M.; Kim, D.-Y. A Study on Entertainment Platform Service Evaluation Using IPA (Importance-Performance Analysis): Focusing on Weverse. *J. Korea Entertain. Ind. Assoc.* **2022**, *16*, 1–17. [CrossRef]
22. Kang, S. The Fans Who Consume 'Communication': The Idol Fan Platform and Reorganization of Fandom. *Korean J. Commun.* **2022**, *66*, 5–56. [CrossRef]
23. James, S. Affective Participation from the In-Between: The Platformization of K-Pop Fandom. *Soc. Media + Soc.* **2025**, *11*, 1–13. [CrossRef]
24. Kim, S.; Hwang, S.; Kim, J. Factors Influencing K-Pop Artists' Success on V Live Online Video Platform. *Telecommun. Policy* **2021**, *45*, 102090. [CrossRef]
25. Bollmer, G.; Tillerson, B. Platform Fandom: Weverse and the Technological Domestication of Fan Community. *Soc. Media + Soc.* **2025**, *11*, 20563051251326689. [CrossRef]
26. Wu, Y.; Li, Y.; Gui, X. "I Am Concerned, But. . .": Streamers' Privacy Concerns and Strategies in Live Streaming Information Disclosure. *Proc. ACM Hum.-Comput. Interact.* **2022**, *6*, 1–31. [CrossRef]
27. Cenfetelli, R. Inhibitors and Enablers as Dual Factor Concepts in Technology Usage. *J. Assoc. Inf. Syst.* **2004**, *5*, 472–492. [CrossRef]
28. Cenfetelli, R.T.; Schwarz, A. Identifying and Testing the Inhibitors of Technology Usage Intentions. *Inf. Syst. Res.* **2011**, *22*, 808–823. [CrossRef]
29. Hagiu, A.; Wright, J. Multi-Sided Platforms. *Int. J. Ind. Organ.* **2015**, *43*, 162–174. [CrossRef]
30. Eisenmann, T.R.; Parker, G.; Van Alstyne, M.W. Strategies for Two Sided Markets. *Harv. Bus. Rev.* **2006**, *84*, 92–101.
31. Parker, G.; Van Alstyne, M.; Choudary, S.P. *Platform Revolution: How Networked Markets Are Transforming the Economy—And How to Make Them Work for You*; W. W. Norton & Company: New York, NY, USA, 2016.
32. Gawer, A.; Cusumano, M.A. *Platform Leadership: How Intel, Microsoft, and Cisco Drive Industry Innovation*; Harvard Business School Press: Boston, MA, USA, 2002.
33. Gawer, A. Bridging Differing Perspectives on Technological Platforms: Toward an Integrative Framework. *Res. Policy* **2014**, *43*, 1239–1249. [CrossRef]
34. Cusumano, M.A.; Gawer, A.; Yoffie, D.B. *The Business of Platforms: Strategy in the Age of Digital Competition, Innovation, and Power*; HarperBusiness: New York, NY, USA, 2019.
35. Vargo, S.L.; Lusch, R.F. Evolving to a New Dominant Logic for Marketing. *J. Mark.* **2004**, *68*, 1–17. [CrossRef]
36. Vargo, S.L.; Lusch, R.F. Service-Dominant Logic: Continuing the Evolution. *J. Acad. Mark. Sci.* **2008**, *36*, 1–10. [CrossRef]
37. Vargo, S.L.; Lusch, R.F. Institutions and Axioms: An Extension and Update of Service-Dominant Logic. *J. Acad. Mark. Sci.* **2016**, *44*, 5–23. [CrossRef]
38. Tiwana, A.; Konsynski, B.; Bush, A.A. Research Commentary—Platform Evolution: Coevolution of Platform Architecture, Governance, and Environmental Dynamics. *Inf. Syst. Res.* **2010**, *21*, 675–687. [CrossRef]
39. Mukhopadhyay, S.; Bouwman, H. Orchestration and Governance in Digital Platform Ecosystems: A Literature Review and Trends. *Digit. Policy Regul. Gov.* **2019**, *21*, 329–351. [CrossRef]
40. Fiske, J. The Cultural Economy of Fandom. In *The Adoring Audience*; Routledge: London, UK, 1992.
41. Liang, Y.; Shen, W. Fan Economy in the Chinese Media and Entertainment Industry: How Feedback from Super Fans Can Propel Creative Industries' Revenue. *Glob. Media China* **2016**, *1*, 331–349. [CrossRef]
42. Edlom, J.; Karlsson, J. Keep the Fire Burning: Exploring the Hierarchies of Music Fandom and the Motivations of Superfans. *Media Commun.* **2021**, *9*, 123–132. [CrossRef]
43. Marconette, J. Why Are Super Fans so Valuable? Available online: https://luminatedata.com/blog/why-are-super-fans-so-valuable/ (accessed on 16 June 2026).
44. Marconette, J. Breaking News: Luminate Releases 2023 Midyear Music Report. Available online: https://luminatedata.com/blog/breaking-news-luminate-releases-2023-midyear-music-report/ (accessed on 12 August 2026).
45. Ham, M.; Lee, S.W. Factors Affecting the Popularity of Video Content on Live-Streaming Services: Focusing on V Live, the South Korean Live-Streaming Service. *Sustainability* **2020**, *12*, 1784. [CrossRef]
46. Liang, F.; Ji, L. Manufacturing Influencers: The Gatekeeping Roles of MCNs (Multi-Channel Networks) in Cultural Production. *Inf. Commun. Soc.* **2024**, *27*, 2297–2313. [CrossRef]
47. Prasetyo, K.; Fauzi, E.P.; Putri, I.H. K-Pop Fandoms Loyalist Phenomenon: Fans Participatory Branding on Social Media Content Practices Distribution in Indonesia. *Paragraphs Environ. Des.* **2023**, *1*, 79–84. [CrossRef]
48. Harrison, D.A.; Mykytyn, P.P., Jr.; Riemenschneider, C.K. Executive Decisions about Adoption of Information Technology in Small Business: Theory and Empirical Tests. *Inf. Syst. Res.* **1997**, *8*, 171–195. [CrossRef]
49. Chwelos, P.; Benbasat, I.; Dexter, A.S. Research Report: Empirical Test of an EDI Adoption Model. *Inf. Syst. Res.* **2001**, *12*, 304–321. [CrossRef]

50. Brous, P.; Janssen, M.; Herder, P. The Dual Effects of the Internet of Things (IoT): A Systematic Review of the Benefits and Risks of IoT Adoption by Organizations. *Int. J. Inf. Manag.* **2020**, *51*, 101952. [CrossRef]
51. Herzberg, F.; Mausner, B.; Snyderman, B.B. *The Motivation to Work*, 2nd ed.; Wiley: New York, NY, USA, 1967.
52. Ban, J. Anatomy of the Three Major Fandom Platforms: Weverse's Scale, Bubble's Substance, and Universe's Gamification. *MK Economy*, 17 September 2021. Available online: https://www.mk.co.kr/news/business/10031854 (accessed on 26 July 2026). (In Korean)
53. Choi, C.-W. The Monetization of Communication: Profitable Fandom Platforms—DearU Versus Weverse. *Maeil Business/MaeKyung Economy*, 6 October 2023. Available online: https://m.mk.co.kr/news/business/10844159 (accessed on 26 July 2026). (In Korean)
54. Park, J.-H. HYBE Versus Kakao: Who Will Win the Profitable Fandom-Platform Market? *Maeil Business Newspaper*, 14 June 2023. Available online: https://www.mk.co.kr/news/culture/10759508 (accessed on 26 July 2026). (In Korean)
55. Kang, S. *Fandom Platforms and Changes in the Digital-Based Entertainment Industry; Media Issue & Trend*; Korea Communications Agency: Naju, Republic of Korea, 2022; Volume 50. Available online: https://www.kca.kr/Media_Issue_Trend/vol50/sub01_01.html (accessed on 26 July 2026). (In Korean)
56. Oh, Y.; Kim, K.-C. Fan Platform Strategy with Fan Experience: Focusing on Weverse. *Korean J. Animat.* **2024**, *20*, 194–209. [CrossRef]
57. Fahey, L.; Narayanan, V.K. *Macroenvironmental Analysis for Strategic Management*; West Publishing: St. Paul, MN, USA, 1986.
58. Saaty, T.L. *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*; McGraw-Hill International Book Company: New York, NY, USA, 1980.
59. Zadeh, L.A. Fuzzy Sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]
60. Van Laarhoven, P.J.M.; Pedrycz, W. A Fuzzy Extension of Saaty's Priority Theory. *Fuzzy Sets Syst.* **1983**, *11*, 229–241. [CrossRef]
61. Buckley, J.J. Fuzzy Hierarchical Analysis. *Fuzzy Sets Syst.* **1985**, *17*, 233–247. [CrossRef]
62. Chang, D.-Y. Applications of the Extent Analysis Method on Fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [CrossRef]
63. Hahn, E.D. Decision Making with Uncertain Judgments: A Stochastic Formulation of the Analytic Hierarchy Process. *Decis. Sci.* **2003**, *34*, 443–466. [CrossRef]
64. Rosenbloom, E.S. A Probabilistic Interpretation of the Final Rankings in AHP. *Eur. J. Oper. Res.* **1997**, *96*, 371–378. [CrossRef]
65. Abdullah, A.G.; Shafii, M.A.; Pramuditya, S.; Setiadipura, T.; Anzhar, K. Multi-Criteria Decision Making for Nuclear Power Plant Selection Using Fuzzy AHP: Evidence from Indonesia. *Energy AI* **2023**, *14*, 100263. [CrossRef]
66. Srđević, B.; Srđević, Z. Evaluating Groundwater Ponds for Urban Drinking Water Supply Under Uncertainty. *Water Supply* **2022**, *22*, 7643–7655. [CrossRef]
67. Forman, E.; Peniwati, K. Aggregating Individual Judgments and Priorities with the Analytic Hierarchy Process. *Eur. J. Oper. Res.* **1998**, *108*, 165–169. [CrossRef]
68. Mühlbach, S.; Arora, P. Behind the Music: How Labor Changed for Musicians Through the Subscription Economy. *First Monday* **2020**, *25*. [CrossRef]
69. Hesmondhalgh, D. Is Music Streaming Bad for Musicians? Problems of Evidence and Argument. *New Media Soc.* **2021**, *23*, 3593–3615. [CrossRef]
70. Bergantiños, G.; Moreno-Ternero, J.D. Revenue Sharing at Music Streaming Platforms. *Manag. Sci.* **2025**, *71*, 8319–8335. [CrossRef]
71. Kwon, S.-J. Big Hit Entertainment's Contents Innovation: Focusing on Entrepreneurial Leadership and Platform Strategy. *J. Korea Entertain. Ind. Assoc.* **2021**, *15*, 1–12. [CrossRef]
72. Lou, C.; Zhou, X. What Else Is New About Social Media Influencers? Uncovering Their Relation and Content Strategies, and the Downsides of Being Famous. *Front. Psychol.* **2024**, *15*, 1437384. [CrossRef] [PubMed]

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