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ARTICLE

UGC metaverse and network effects: Complementary interaction in the avatar market – A case study from VRChat

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Abstract – Although User-Generated Content (UGC) metaverse markets exhibit structural features that platform theory associates with network effects-driven concentration, empirical evidence on whether, and how, such concentration emerges in this context remains scarce. As a preliminary empirical investigation, this paper takes VRChat as the leading exemplar of a UGC metaverse, where avatars and compatible outfits are produced by independent creators and traded on external e-commerce, and examines how outfit creators allocate production effort across the avatar landscape over time. We propose a UGC metaverse network effects framework distinguishing direct and indirect network effects, and analyze the top 100 avatars from 2023 to 2025 using two complementary diagnostics: the Herfindahl-Hirschman Index as a creator-level static descriptor, and an avatar-level power-law regression of later on initial outfit stock as a dynamic descriptor of cumulative advantage. We document a divergence: although the static creator-level distribution remained stable despite a more than threefold market expansion, the avatar-level growth elasticity shifted significantly across year-pairs ($\Delta\gamma = 0.20$, paired bootstrap 95% CI [0.06, 0.35], $p = 0.003$), rising from $\gamma = 0.81$ in 2023–2024 (95% CI [0.66, 0.95]) to $\gamma = 1.01$ in 2024–2025 (95% CI [0.99, 1.03]). The 2023–2024 estimate lies significantly below 1, consistent with a sublinear regime in which mid-tier avatars closed the gap with incumbents; the 2024–2025 estimate is essentially at the proportional-growth threshold. Within this preliminary scope, the shift is consistent with weakening avatar-level catch-up dynamics; it does not demonstrate increased creator-level concentration. The principal policy implication is that competition assessment of UGC metaverse markets should not rely on static metrics alone; avatar-level growth-elasticity dynamics, alongside creator-level concentration metrics, merit forward-looking monitoring, particularly for interoperability standards and market contestability. Whether the shift represents a transient redistribution or the early stage of sustained concentration cannot be resolved with the present data, warranting continued observation.

Keywords – Avatars, complementary goods, metaverse, network effects, user-generated content

1. INTRODUCTION

In recent years, along with the expansion of activities in metaverse and virtual spaces (hereinafter referred to as “metaverse”), the market for 3D avatars (hereinafter, “avatars”), which are downloadable digital content, has been rapidly growing. The use of avatars and the customization of outfits in the metaverse have widely been recognized as a form of self-expression, and it has been pointed out that these practices may contribute to realizing a society free from discrimination based on physical or social attributes [1, 2]. Research has shown that users exhibit higher self-similarity when utilizing customized avatars [3]; additionally, an avatar’s attractiveness has been demonstrated to positively influence impression formation [4]. Because users often design and create avatars reflecting their own personalities, several studies argue that the breadth of avatar customization is a critical factor in enhancing a platform’s competitive advantage [5, 6]. As of the end of December 2024, VRChat [7], a representative metaverse, places emphasis on User-Generated Content (UGC). Consequently, as illustrated in Fig. 1 (adapted from the author's prior work [55]), transactions involving avatars and outfits are conducted on a platform distinct from the metaverse itself. Moreover, as shown in Fig. 2

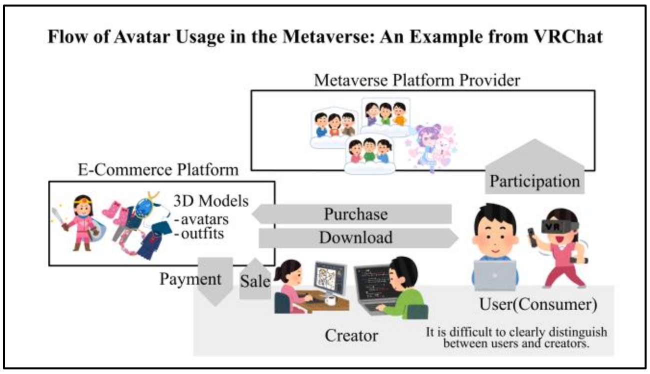

Figure 1 – Flow of Avatar Usage in the Metaverse: An Example from VRChat

(adapted from [55]), the parties selling avatars and outfits are not necessarily the same, and in general, because each avatar can differ in its skeleton (rig) or other configuration, outfits do not universally fit all avatars. In order to make an outfit compatible with a specific avatar, detailed setup of the outfit is required. Typically, outfits are sold with labels such as "Outfit compatible with [some avatar name]," although there are instances where a single outfit can be adapted for multiple avatars [8]. While it is not technically impossible, given the relevant licensing terms and sufficient technical skill on the part of the purchaser, to modify an outfit post-purchase to suit the user's preferred avatar, this paper does not take that possibility into consideration.

Building on prior studies showing that a platform can strengthen its market position by supplying its own complementary products and limiting independent complementors' access to users, a setting in which the platform operator coexists with many autonomous avatar and outfit creators appears, at first glance, counter-intuitive from a profit-maximization perspective for the platform itself [9, 10]. However, empirical evidence from VRChat points in a different direction. According to [11], which compares various virtual worlds based on a metaverse maturity model, where VRChat's "Economy" rating is the lowest score of 1 (on a scale of 1–5) despite having a high score of 4 in "User-Generated Content", the fact that VRChat has continued to gain user support and expand its user base beyond the period of peak public attention to metaverse platforms in 2021-2022 [12] suggests that the kind of market structure shown in Fig. 1, which prioritizes user-generated content, may remain favored by users and persist as a mainstream approach.

We use the term UGC metaverse to denote a metaverse environment satisfying all three of the following structural conditions: (i) avatars and outfits are produced by independent third-party creators rather than by the platform operator; (ii) transactions of these complementary goods occur on external e-commerce platforms rather than within the metaverse itself; and (iii) users can upload acquired avatars and outfits to the platform for use. Under this definition, VRChat is the leading exemplar and the focus of the present case study. Second Life satisfies condition (i) but conducts transactions on an internal marketplace economy denominated in Linden Dollars, and therefore does not satisfy condition (ii); it is structurally distinct from the case examined here. Platforms such as Fortnite and Roblox handle avatar acquisition and cosmetic transactions through platform-internal pipelines and do not permit user-side import of externally-acquired avatars; they fail conditions (ii) and (iii) of our definition, and the issues of cross-platform interoperability and switching-cost lock-in that we analyze are not directly applicable to those cases.

At the same time, it is not obvious that canonical platform theories can be transplanted to a UGC metaverse without adjustment.

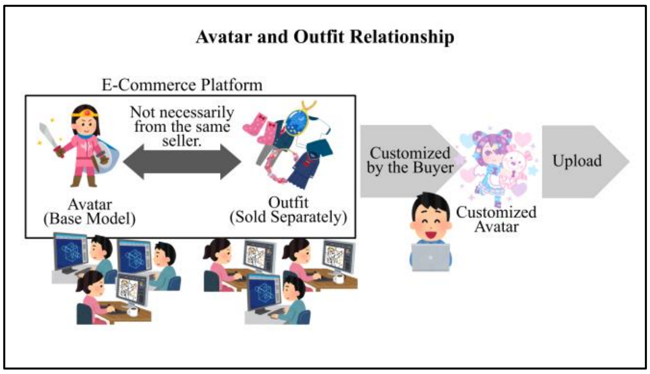

Figure 2 – Avatar and outfit relationship

In recent electronic commerce, downloadable digital content has become a primary object of transactions, raising a wide range of issues including consumer protection, intellectual property rights, and transactional transparency. Furthermore, because many e-commerce platforms involve two-sided or multi-sided market structures, competition policies, rules among operators, and fee models within those platforms exert significant influence on consumer welfare and overall market integrity. The avatar market embedded within a UGC Metaverse also strongly exhibits these structural characteristics of electronic commerce. Hence, it is believed to be closely related to academic frameworks such as network effects and platform theory; however, literature analyzing these relationships remains extremely limited.

2. RESEARCH OBJECTIVES AND CONTRIBUTIONS

Since around 2020, the field of avatars intended for use in the metaverse has drawn increasing attention in policy practice. In Japan, for instance, the National Institute of Advanced Industrial Science and Technology has established a domestic committee to discuss the international standardization of avatars, and at the international level, the International Telecommunication Union (ITU) has launched the ITU Focus Group on metaverse (FG-MV). Within these discussions, topics such as avatar compatibility are also under review [13, 14].

Despite this policy attention, empirical evidence on how network effects shape concentration in UGC metaverse markets is scarce. Canonical platform theory predicts that strong network effects drive markets toward oligopoly [16, 23], yet whether this prediction holds in a market characterized by independent creators, external e-commerce, and avatar outfit complementarity remains an open question.

We approach this question through what is directly observable in our data: the allocation decisions of outfit creators, how independent third-party producers distribute their production effort across the avatar landscape. Under the canonical network effects mechanism, creators would allocate disproportionately and increasingly toward avatars they expect to attract users, producing concentration in the cross-creator distribution of outfit production.

This paper addresses two related questions. The first is whether the cross-creator allocation of compatible outfits in the VRChat avatar market exhibits the concentration trajectory predicted by canonical network effects theory. The second is what the temporal evolution of this allocation implies for competition policy. We address these questions using two diagnostics that deliberately operate at different levels of aggregation. First, we compute the HHI at the avatar-creator level, after aggregating compatible-outfit counts from the ranked avatar set to the creators who produced those avatars. This captures whether compatible outfit allocations are concentrated among a small number of avatar creators at each snapshot. Second, we estimate an avatar-level power-law relationship between initial compatible outfit stock and later compatible outfit stock. This captures whether individual avatars with larger incumbent stocks subsequently accumulate compatible outfits more or less than proportionally. We report both diagnostics because creator-level concentration may remain stable even when avatar-level growth dynamics change.

Specifically, this study pursues three objectives.

(1) Conceptual synthesis: Integrate existing theories of network effects, complementary goods, and switching-cost lock-in into a unified framework for user-generated metaverse markets [15, 16].

(2) Exploratory quantification: Analyse the cross-creator distribution of compatible outfits in VRChat and its temporal evolution by computing the Herfindahl–Hirschman Index (HHI) as a static descriptor and the power-law growth elasticity as a dynamic descriptor, for the top 100 avatars (2023–2025). The volume of compatible outfits per avatar is treated not as a proxy for user-base size but as a direct observable indicator of how outfit creators allocate production effort across the avatar landscape, that is, of the cross-creator distribution of effort that the indirect network effect between avatars and outfits is hypothesized to shape.

(3) Policy implications: Derive preliminary electronic-commerce policy implications regarding interoperability standards and platform contestability.

Questions about whether positive network feedbacks necessarily push digital markets toward oligopoly or monopoly, and about whether regulatory intervention is warranted, have been central to platform scholarship since its formative years [17, 18, 19, 20, 21, 22, 23, 24]. The canonical answer, that they often do, is itself contested in the more recent literature, which documents stable multi-platform equilibria sustained by horizontal differentiation and multi-homing [43, 44]. Whether VRChat's avatar market follows the canonical trajectory or admits a stable non-concentrated equilibrium is itself an open empirical question that this paper takes up. By treating avatars and their complementary outfits as a coupled system, this study provides early empirical evidence, based on 2023–2025 VRChat data, on whether the observed dynamics align with the canonical model in which value rises monotonically with user base or diverge toward a more heterogeneous equilibrium. These preliminary findings aim to inform ongoing debates on interoperability standards and competition policy in the metaverse.

This exploratory study recognises that longitudinal data is scarce and formal theory is still emerging; its principal contribution is to document the market structure of VRChat, a leading UGC metaverse platform, and to provide stylized empirical facts that can guide analyses of other user-generated virtual economies.

3. LITERATURE REVIEW AND HYPOTHETICAL FRAMEWORK

3.1 The “intrinsic value” of the avatar itself and the additional value provided by outfits

In this section, we organize existing digital platform theories that are instrumental in understanding the avatar market, namely network effects, the theory of complementary goods, and lock-in theory. When considering the relationship between avatars and the outfits designed to be compatible with them, each of these theories explains various aspects of market structure, competition, and user behavior from different angles.

Before turning to the avatar outfit relationship, it is useful to clarify why this market falls within the scope of economic analysis at all. Avatars and outfits in VRChat are digital goods whose marginal reproduction cost is near zero, and one might therefore question whether they raise an economic-allocation question in the conventional sense. The established literature on virtual goods and information goods answers this in the affirmative. Shapiro and Varian [31] show that information goods markets, despite negligible reproduction costs, are subject to standard microeconomic dynamics, pricing, differentiation, lock-in, network effects, and require corresponding familiar analytical tools. Lehdonvirta [35] and Lehdonvirta and Castronova [51] extend this argument to virtual goods specifically, demonstrating that the relevant scarcity in virtual economies is typically not in the goods themselves but in adjacent resources: developer-imposed access controls, attention, status, and creator effort. In the VRChat avatar outfit market, the reproduction cost of any specific outfit is indeed close to zero, but the production effort of independent outfit creators, finite hours of design, modeling, rigging, and compatibility testing, is the scarce resource whose allocation across the avatar landscape this paper examines. The economic question is therefore not how a fixed stock of outfits is divided, but how creators distribute their finite production capacity across competing avatar targets, and how that allocation pattern evolves under the network effects and complementarity dynamics described below.

In particular, the "complementary goods model," frequently illustrated using the "hardware and software" relationship, closely parallels the connection between avatars and outfits; however, it is not an exact overlap. The key distinction is that the avatar itself already possesses standalone utility, while the outfit serves as an additional element that "further expands or customizes" it [25]. For users, outfits offer added benefits such as: (1) greater freedom to alter appearances, (2) enhancement of character identity or brand image, and (3) alignment with a particular worldview or event. The stronger these added benefits, the stronger the indirect network effect operating between avatars and outfits is hypothesized to be, creating a potential incentive for users to concentrate on certain avatars. Prior studies establish that the breadth of avatar customization enhances a platform's competitive advantage [5, 6] and that customization options drive user immersion, satisfaction, and loyalty in virtual environments [33, 34]. These findings, however, concern customization availability at the platform or environment level; they do not directly test whether, within a single platform, the specific avatars that accumulate more compatible outfits thereby acquire greater individual appeal or attract disproportionate user attention.

Accordingly, this chapter aims to: (1) assume the avatar's individual value as a baseline, (2) explore how the addition of outfits creates a complementary relationship and amplifies network effects, and (3) examine how user lock-in and platform influence might lead to market oligopoly. Our discussion will integrate established economic theories, such as network effects and complementary goods, with platform strategy concepts like lock-in. This synthesis serves as a preliminary step toward developing a unified analytical framework for analyzing the 3D avatar market and considering its potential applications and policy implications.

3.2 Direct network effects and indirect network effects

Network effects (also referred to as network externalities; hereinafter, "network effects") refer to the phenomenon in which the benefit to existing users increases as the number of people utilizing a product or service grows. Generally, direct network effects appear in services such as SNS or communication platforms, where the value to each participant rises as the number of co-participants on the same network grows. In contrast, indirect network effects arise from the interaction between a main product and its complementary goods, where increased adoption of the main product expands the supply of complements and thereby raises its value [26].

That the metaverse itself exhibits direct network effects has already been shown in [27], and it is only natural that its value improves as the number of metaverse users increases. However, in this paper, we newly focus on the relationship between avatars and outfits, which likely constitutes an indirect network effect. The reason is that if a particular avatar gains popularity, outfit creators acquire a heightened incentive to produce outfits compatible with that avatar, leading to a larger variety of outfits. For instance, [28] and [29] observe in platform markets that third-party developers tend to concentrate their software development efforts on platforms boasting a sizable user base.

In the 3D avatar market, therefore, the incentive for outfit creators to focus on popular avatars, perceived as likely to command a large potential customer base, further accelerates the concentration of outfits around popular avatars, presumably amplifying network effects. Moreover, this synergistic cycle of avatars and outfits may also contribute to user expansion within the UGC metaverse itself. We acknowledge, however, that the route from outfit availability to platform-level user adoption i.e., whether users select VRChat over alternative metaverses on the basis of avatar customization breadth, is not testable with our data, which capture only the within-platform avatar outfit market. Our framework therefore makes claims about the avatar outfit relationship inside VRChat (the right-hand side of Fig. 3); the link from this relationship to platform-level user growth (the left-hand side) is presented as a conjectured connection in the conceptual framework, not as an empirically supported claim of this paper. Fig. 3 illustrates these dual-layered network effects, which we propose as "The UGC metaverse network effects framework."

From a theoretical perspective, both positive externalities (benefits that increase with adoption) and negative externalities (congestion or higher search costs) are possible. In the VRChat avatar outfit market studied here, however, avatars and their complementary outfits are sold on external e-commerce sites such as BOOTH, where searching, payment, and downloading are completed entirely within each site's interface. Because these goods are downloadable digital content, no large-scale production facilities are required; hence a surge in demand is unlikely to slow delivery or create congestion. We therefore assume that negative externalities are structurally limited and that positive externalities predominate. Although an unexpectedly sharp rise in user numbers could eventually surface negative externalities in the form of increased server load on VRChat, that possibility lies outside the scope of this paper.

Indirect network effects do not necessarily retain a constant sign or magnitude. Reference [30] shows that the network effects between mobile social-networking services and smartphones are positive before the market reaches its peak but turn negative afterward. According to [30], this reversal occurs because (i) in the early diffusion phase complementary goods help the platform achieve critical mass, whereas (ii) in later phases market saturation yields diminishing marginal utility and stronger competition from substitutes. As noted above, VRChat has continued to expand its user base even after the initial "metaverse boom," so the platform can still be regarded as pre-peak; positive externalities are therefore the expected outcome.

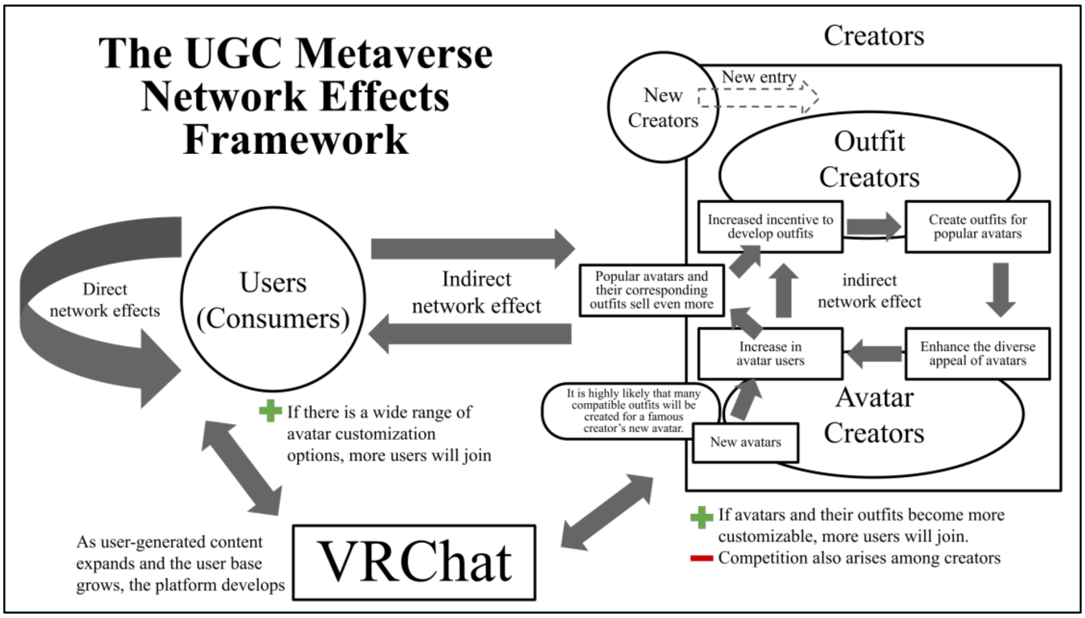

Figure 3 – The UGC metaverse network effects framework
[For VRChat]

3.3 Standardization and compatibility issues

A frequently raised topic in complementary goods models is how "the presence or absence of compatibility" significantly impacts market structure [31]. Once a user adopts a particular product, learning and additional investment often increase switching costs, giving rise to what is termed lock-in [32]. In the digital economy, a typical example would be purchasing music or e-books that cannot be easily used on another platform. In this paper's context, if a user possesses many outfits designed for Avatar A, the issue of "having to repurchase outfits" when switching to Avatar B parallels this phenomenon. The compatibility issue thus has the potential to further reinforce the indirect network effects shown in the UGC metaverse network effects framework (Fig. 3).

3.4 A hypothetical model of avatar utility

Based on the above analyses, we propose a simplified utility model to structure the various factors at play. We emphasize that this model is presented as a conceptual scaffold for interpretation, not as a structural specification to be estimated within this paper. The coefficients (β, η, ζ, λ) are introduced to organize the discussion of how outfits, compatibility, creator brand power, and switching costs may jointly shape user choice; their signs and relative magnitudes are conjectures grounded in prior literature [33–39] rather than estimates from our data. Our subsequent quantitative analysis (Section 4) examines two observable implications of this scaffold: the creator-level cross-sectional distribution of compatible outfit allocations, and the avatar-level dynamic relationship between initial outfit stock and later accumulation. The former is summarized by the HHI, whereas the latter is summarized by the power-law elasticity. The remaining components of the scaffold are treated as scope-limited conjectures whose direct measurement is left to future research (Section 5.4). The model describes user i's utility (benefit) when selecting a new avatar j:

$$U_{ij} = \alpha_j + \beta x_j + \eta f(s_j) + \zeta g(k_j) - \lambda c_{ij} + \varepsilon_{ij} \quad (1)$$

Our subsequent quantitative analysis focuses on the observable implications of this framework, specifically using the number of outfits (xj) as a direct observable indicator of how outfit creators allocate production effort across avatars, representing a first step toward understanding the broader dynamics suggested by the model.

In this formulation, α_j is a constant term representing the "baseline appeal" of the avatar, specifically encompassing factors such as design quality and initial features [33], but excluding price factors. x_j is an index indicating the variety or total number of outfits related to avatar j. The larger this value is, the wider the range of customization is assumed to be [34]. Meanwhile, β represents the degree to which the avatar's appeal may rise as the number of outfits increases. Following the convention in prior literature [35], β is conjectured to be positive ($\beta > 0$); this sign is a hypothesis rather than an estimate from our data. $\eta f(s_j)$ captures users' expectations for future development based on the extent of outfit compatibility. An avatar whose outfit compatibility sj is high (e.g., via adopting a common standard [36]) may become usable with a wider range of outfits and related content going forward, which is hypothesized to enhance user utility. On the other hand, $\zeta g(k_j)$ reflects the hypothesized influence of the brand power of the avatar's creator. Prior literature [37] suggests that an avatar produced by a well-known creator may receive more additional outfits in the future, although our data does not distinguish creator brand effects from other determinants. Finally, $-\lambda c_{ij}$ denotes the switching cost incurred by user i upon moving to avatar j. This switching cost c_{ij} may involve the need to repurchase outfits if those already owned do not align with the new avatar; if the user has not previously purchased any avatar or outfit, it becomes zero. A higher cost leads to a reduction in utility. ε_{ij} is a stochastic component capturing user i's idiosyncratic preferences [38] or choice-related errors. Following the standard extreme value assumption in [39], ε_{ij} is conventionally modeled as a Type I extreme value (Gumbel) variate, which would yield closed-form multinomial-logit choice probabilities should this scaffold later be operationalized as an estimable model. Under this assumption, U_{ij} would be handled as a probabilistic choice model.

3.5 An integrated hypothesis: Application to the 3D avatar market

By combining the foregoing theories, network effects, the theory of complementary goods, and lock-in, it becomes apparent that the 3D avatar market exhibits several distinctive structures. First, the avatar itself possesses a certain standalone value. Even without adding any outfit, i.e., the avatar in its initial state right after purchase, users can still engage in communication and express a character, which implies that this setting differs somewhat from the stronger forms of interdependence often observed in other industries. Nonetheless, the addition of outfits is hypothesized to yield a "complementary" relationship that may raise the avatar's appeal, potentially creating an indirect network effect: as the number of users increases, the selection of outfits could expand, and as the number of outfits grows, the avatar's inherent value could also rise. Whether this hypothesized loop operates in the VRChat data is the question we examine in Section 4.

Moreover, if the availability of outfits broadens the range of avatar customization and makes the avatar itself more attractive, a feedback loop could emerge in the form of "popular avatar → enriched outfits → even greater popularity." Should users come to expect that "outfit creators will develop compatible outfits for any new avatar from a creator renowned for producing popular avatars," this could raise the theoretical possibility of certain creators dominating the market (oligopolization). Poor compatibility among outfits would, under this scenario, intensify user switching costs (lock-in). From the viewpoint of outfit creators, the canonical platform-economics literature [28, 29, 40] suggests an incentive to focus on outfits for popular avatars (and any new avatar produced by a successful creator), under the assumption that they target a larger potential customer base. We treat this as a hypothetical mechanism to be examined empirically in Section 4, not as an established characterization of VRChat creator behavior, which we cannot directly observe in our data.

If both "users preferring avatars that accommodate numerous outfits" and "outfit creators prioritizing popular avatars" hold simultaneously, the resulting two-way motivation could further amplify indirect network effects. Under this scenario, later entrants, both new avatars and new creators, would face a disadvantage, and an avatar (and its creator) that once achieves a significant share of compatible outfits could potentially come to dominate the market. We do not, however, claim that this scenario has materialized in our data; whether the observed dynamics are consistent with such a trajectory is taken up in Section 5.

The hypothetical utility model presented in this chapter conjectures that outfits, acting as complementary goods, may enhance an avatar's appeal ($\beta > 0$), and that the presence of robust lock-in (λc_{ij}) could facilitate progression toward oligopoly. The literature also suggests that outfit creators have an incentive to "prioritize popular avatars," related to $\zeta g(k_j)$ (brand power), which would reinforce the user's expectation that "this creator will keep adding many outfits." Our data, however, do not contain sales figures, individual user choices, or direct measures of avatar popularity. What we observe is the cross-sectional distribution of compatible outfits across creators, that is, the revealed allocation decisions of outfit creators across the avatar landscape. We use this distribution, and its evolution over time, to examine which patterns are consistent with the hypothesized network-effects mechanism. Although this research is exploratory in nature and limited to hypothesis proposals plus a degree of empirical validation, we plan to conduct an empirical data analysis along the following three avenues:

- Degree of outfit concentration on each avatar

  Determine which creator's avatars have how many compatible outfits.

- Extent to which concentration favours specific creators

  By assessing whether outfits are primarily concentrated in top-ranked creators or instead spread across numerous mid-level creators, we investigate signs of popularity concentration due to ($\beta > 0$).

- Oligopolization (lock-in) across the overall market

  We use the HHI to compare market structures from 2023 to 2025, determining whether the market has become more concentrated or whether diversity remains. Through this approach, we infer the extent to which lock-in (λc_{ij}) is operative.

Through these approaches, we aim to partially validate, via data analysis, the hypothesis of indirect network effects wherein "popular avatars (and newly introduced avatars from those creators) attract an increasing share of outfits as the overall market grows over time," and to draw implications from the perspective of electronic commerce policy. The following chapter provides detailed explanations of the datasets and methodologies used.

4. PRELIMINARY MARKET INVESTIGATION

4.1 Method

The theory of complementary goods suggests that the more compatible outfits an avatar offers, the stronger its indirect network effects become for the user who selects that avatar. In this study, we visualize the degree to which each avatar creator has attracted outfits by aggregating the "number of compatible outfits" at the creator level, thereby gauging the concentration of popular avatars. If the lock-in effect discussed in this research is robust, then once an avatar creator achieves a substantial share of compatible outfits, the market may converge in a single direction (leading to oligopoly or monopoly). To examine this possibility, we calculate the HHI using the number of compatible outfits per creator on 18 May 2023, 27 December 2024, and 30 May 2025, and then statistically test whether the observed changes in market concentration are significant.

In this paper, we analyze the number of avatars and their corresponding outfits by focusing on 3D models intended for use in “VRChat.” These models are sold on “BOOTH,” a prominent 3D model sales platform for UGC metaverse content that is widely utilized in Japan and Korea. According to the 2025 BOOTH 3D Model Category Market White Paper, the transaction volume in 2024 amounted to JPY 5.8 billion [41].

Table 1 – Definitions of objects and measurement

Symbol / Term	Definition
Avatar	A 3D model with a unique rig configuration, sold as a downloadable digital good for use in VRChat.
Avatar creator	The producer of one or more avatars. A single creator may release multiple avatars over time.
Outfit	A clothing or accessory item sold separately as a digital good, configured to be compatible with one or more specific avatars. Produced by outfit creators, who are in general distinct from avatar creators.

4.2 Data collection

We gathered market data at three snapshots, 18 May 2023, 27 December 2024, and 30 May 2025, from BOOTH product listings and from Avatar Network, a community-maintained reference site that aggregates avatar outfit compatibility metadata. At each snapshot, we counted, for every avatar listed on BOOTH, the number of outfits whose product page declares compatibility with that avatar; outfits compatible with multiple avatars are counted once for each declaration. Avatars were then ranked by this compatibility count, and the top 100 were retained. The ranked set is constructed independently at each snapshot and is therefore not panel-balanced; for the power-law regression noted in Section 4.3.3, this is addressed by restricting the primary specification to a balanced subset of avatars present in all three snapshots. When an avatar dropped out of the top 100 at a subsequent snapshot, we did not retroactively retrieve its outfit count, so the HHI in Section 4.3.2 is computed within each snapshot's top 100 set independently. Bootstrap procedures (10,000 iterations) are used to test differences in HHI across snapshots in Section 4.3.2 and to construct confidence intervals for the power-law elasticity note in Section 4.3.3; details of the resampling scheme are described in those sections.

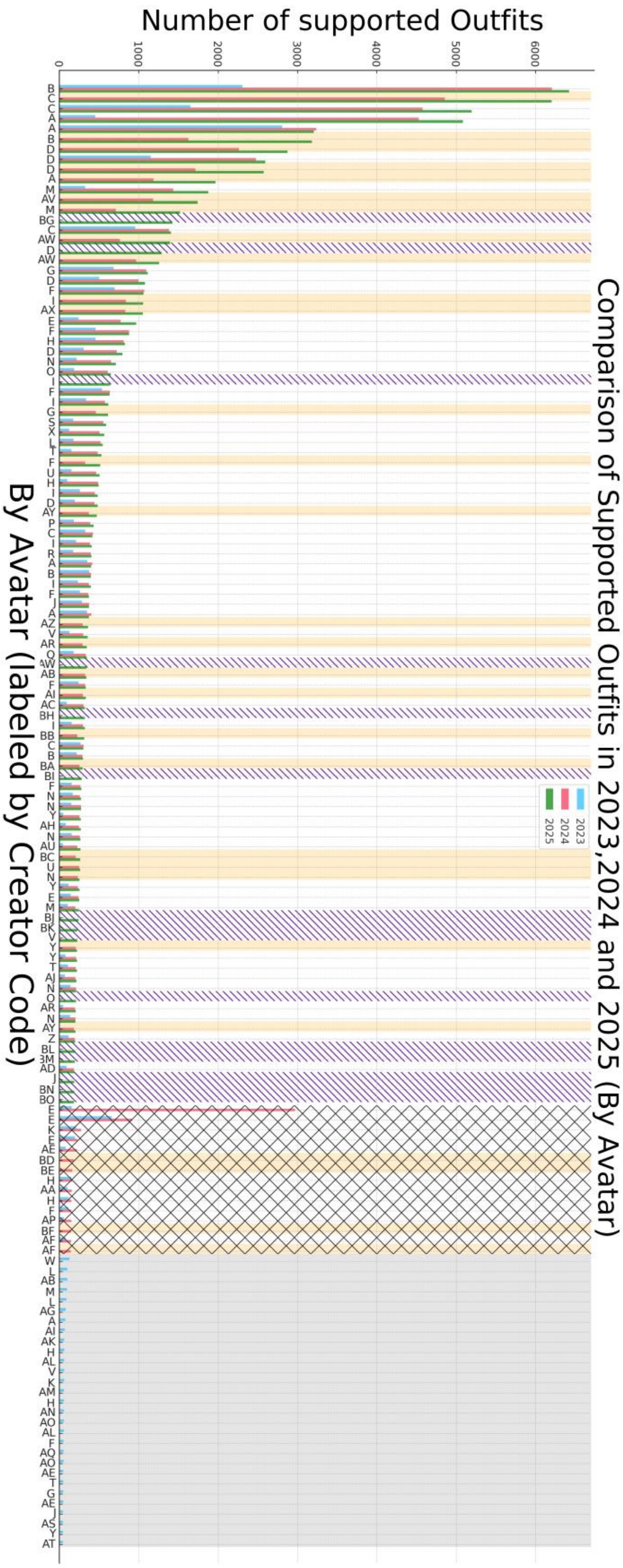

Figure 4 – Comparison of supported outfits in 2023, 2024, and 2025 (by avatar)

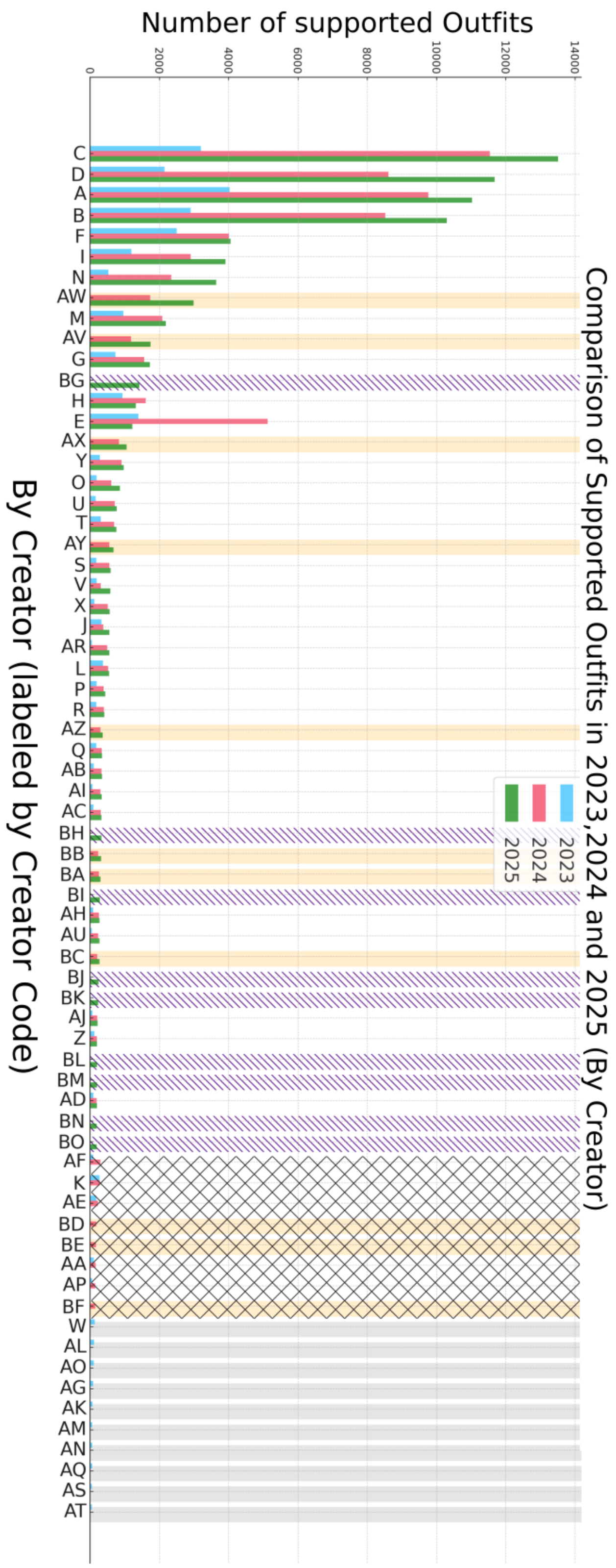

Figure 5 – Comparison of supported outfits in 2023, 2024, and 2025 (by creator)

4.3 Analysis

4.3.1 Data overview

First, Fig. 4 is a grouped bar chart demonstrating how the top 100 avatars, ranked by the number of compatible outfits, changed between 2023, 2024, and 2025. The sections with a gray background indicate avatars that were in the top 100 in 2023 but fell below the 100th position in 2024. The sections with a gray hatched background indicate those that were in the top 100 in 2024 but fell below that position in 2025. Because they dropped below 100th place, their data for the corresponding year are excluded from the collection, causing missing values. The sections highlighted in orange denote avatars that were ranked below 100th place in 2023 (or had not been released yet) but reached the top 100 in outfit counts by 2024. Similarly, the sections with a purple hatched background denote avatars that newly entered the top 100 in 2025. The vertical axis shows the number of compatible outfits, while the horizontal labels are alphabetical identifiers for each avatar's creator.

Next, Fig. 5 consolidates the grouped bar chart (Fig. 4) by creator. The gray, orange, and purple shading follows the same significance as in Fig. 4. In some cases, a single creator might release multiple avatars that each rank among the top 100 for compatible outfits; collating this data by creator, as in Fig. 5, allows for a more accurate assessment of market concentration. According to Figs. 4 and 5, the number of compatible outfits per avatar has increased sharply over the two-year period, indicating that the market size is growing rapidly. However, this also suggests that the high-level market structure, particularly at the top, may not have undergone significant changes.

An examination of the collected data reveals that the number of compatible outfits for the top 100 avatars increased from 25157 to 85436. Over a two-year period, this represents a more than threefold increase in the number of compatible outfits, suggesting overall market growth, the entry of new creators, and an upsurge in production activities. A decrease in supported outfits, such as that seen for creator E in Fig. 4, occurs when the corresponding avatar creator discontinues the sale of a specific avatar.

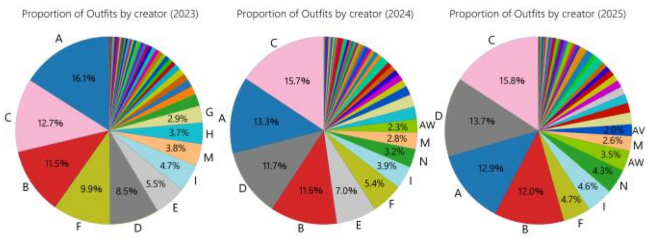

Figure 6 – Proportion of compatible outfits attributed to each avatar creator

Drawing on Fig. 5, Fig. 6 provides a pie chart illustrating the share of compatible outfits for each creator. For consistency, the same color is assigned to any creator whose name appears in both 2023 and 2024. To maintain clarity, only the top 10 creators are labeled with an alphabetic identifier and a corresponding percentage.

4.3.2 HHI

Next, to evaluate the structural changes in the market (i.e., to see if oligopolization has advanced) on a statistical basis, we calculated the HHI.

$$HHI_t = 10{,}000 \times \sum_{i=1}^{N} s_{i,t}^2, \quad s_{i,t} = \frac{x_{i,t}}{\sum_{j=1}^{N} x_{j,t}} \quad (2)$$

Where $x_{i,t}$ denotes the count of compatible outfits attributed to avatars produced by creator i in snapshot t, (as defined in Section 4.1), and $s_{i,t}$ denotes the corresponding share within the top 100 avatar set.

The results showed that the market HHI was 827.74 in 2023, 833.51 in 2024, and 855.12 in 2025. To test for significant differences in these annual HHI values, we conducted bootstrap hypothesis tests with 10,000 resampling iterations. The observed differences in HHI were 5.77 for 2023 vs 2024 (p = 0.976), 27.38 for 2023 vs 2025 (p = 0.883) and 21.61 for 2024 vs 2025 (p = 0.909). No statistically-significant differences were found in any of the comparisons at the 5 % level. Generally speaking, an HHI below 1500 is, under standard merger guideline thresholds [42], in the unconcentrated range, indicating that the cross-creator distribution is consistent with competition functioning.

Table 2 – HHI for each dataset, total number of outfits

YY/MM/DD	Outfit	HHI
2023/5/18	25157	827.74
2024/12/27	73528	833.51
2025/5/30	85436	855.12

Beneath this aggregate stability, mid-tier ranking shifts have occurred, as visually evident in Figs. 4 and 5. The picture is one in which outfit creators continue to concentrate the bulk of their production effort on a small set of incumbent avatars, while turnover among mid-tier creators absorbs a portion of the market's growth. Interpreted collectively, these static findings are consistent neither with the canonical "oligopoly has further progressed" trajectory nor with full diversification of allocation behavior. Whether this static stability also holds dynamically, that is, whether the trajectory of allocation favors incumbents at an accelerating rate, is the question we turn to next.

4.3.3 Power-law relationship between stock and growth

The HHI summarizes the cross-creator distribution of compatible outfits at a snapshot but says little about how that distribution evolves at the level of individual avatars. The cumulative-advantage question concerns whether individual avatars with larger incumbent stocks of compatible outfits subsequently end up with proportionally more, less, or the same share of compatible outfits, that is, whether the rich-get-richer dynamic operates in this market at the avatar level. Because outfit creators allocate their production effort with respect to specific avatars rather than to creator portfolios, the natural unit of analysis for cumulative advantage is the avatar.

A power-law growth process implies a constant-elasticity relationship between an avatar's incumbent stock at the start of a window and its stock at the end:

$$Y_{end} = c \cdot Y_{start}^{\gamma} \quad (3)$$

where Y_{start} and Y_{end} are the avatar's compatible-outfit counts at the start and end of the observation window, and γ is the elasticity of end-of-window stock with respect to start-of-window stock. The exponent γ has a direct interpretation. When $\gamma = 1$, growth is proportional and the relative ordering of avatars is preserved on average. When $\gamma < 1$ (sublinear), avatars with smaller incumbent stocks gain proportionally more, so the cross-avatar distribution compresses. When $\gamma > 1$ (superlinear), avatars with larger incumbent stocks gain proportionally more, and the distribution stretches further apart. The power-law specification is standard in the empirical literature on city sizes, firm growth, and citation distributions [52, 53, 54], where the question of cumulative advantage is central.

We estimate equation (3) in log-log form by ordinary least squares for each consecutive snapshot pair. The primary regression is restricted to a balanced panel of avatars present in the top-100 ranked set in all three snapshots (n = 61). This restriction ensures that the same avatars' trajectories are compared across the two windows. Because the specification regresses log Y_{end} directly on log Y_{start}, all 61 avatars in the balanced panel are usable in both windows; in particular, avatars whose stock declined within a window ($Y_{end} < Y_{start}$) are still included, since both Y_{start} and Y_{end} are strictly positive. The balanced panel accounts for 85% of compatible outfits in 2023, 63% in 2024, and 58% in 2025; the declining coverage reflects the entry of new avatars into the top ranks rather than attrition from the balanced set.

The point estimates are $\gamma_{23\to24} = 0.81$ and $\gamma_{24\to25} = 1.01$ (Table 3). To assess precision and the robustness of the apparent shift, we compute paired bootstrap confidence intervals (10000 iterations, with avatar-level resampling that preserves trajectory pairing across the two windows). The 95% bootstrap CIs are $\gamma_{23\to24} \in [0.66, 0.95]$ and $\gamma_{24\to25} \in [0.99, 1.03]$. The first interval excludes $\gamma = 1$, indicating that the 2023–2024 window was characterized by clearly sublinear growth at the avatar level: smaller-stock avatars were gaining proportionally more compatible outfits than larger stock avatars. The second interval is tightly centered on 1, indicating that the 2024–2025 window is essentially indistinguishable from proportional growth.

The change in elasticity is the empirically more identifiable quantity. The observed difference $\Delta\gamma = \gamma_{24\to25} - \gamma_{23\to24} = 0.20$ has a paired bootstrap 95% CI of [0.06, 0.35], excluding zero, with two-sided p = 0.003. The shift in growth elasticity between the two windows is therefore statistically distinguishable from zero at the 1% level, with the avatar-level dynamic regime moving from sublinear catch-up toward proportional growth. Fig. 7 illustrates this shift on log-log axes: the regression line for the 2024 → 2025 window has a slope close to 1 (parallel to the diagonal of proportional growth), while the 2023 → 2024 line has a visibly shallower slope.

We re-ran the regression under two alternative specifications as sensitivity checks. First, the full avatar panel including avatars active in only some snapshots gives $\gamma_{23\to24} = 0.83$ (n = 72) and $\gamma_{24\to25} = 1.05$ (n = 86), with the same direction of shift. Second, excluding the single avatar with the largest 2023 stock yields $\Delta\gamma = 0.19$ (95% CI [0.05, 0.37], paired bootstrap p = 0.007), confirming that the result is not driven by a single outlier. The direction $\Delta\gamma > 0$ is therefore consistent across these specifications.

Table 3 – Power-law regression: estimates and uncertainty (primary specification: avatar-level balanced panel)

Quantity	Estimate	95% bootstrap CI	n
$\gamma_{23\to24}$	0.81	[0.66, 0.95]	61
$\gamma_{24\to25}$	1.01	[0.99, 1.03]	61
$\Delta\gamma = \gamma_{24\to25} - \gamma_{23\to24}$	0.20	[0.06, 0.35]	(paired bootstrap p = 0.003)

Notes: Primary specification = balanced panel of avatars present in the top 100 ranked set in all three snapshots. Specification: $\log Y_{end} = \log c + \gamma \cdot \log Y_{start}$. CIs computed by paired bootstrap with 10,000 iterations, with avatar-level resampling. Scale factors: $c_{23\to24} = 5.94$, $c_{24\to25} = 1.02$.

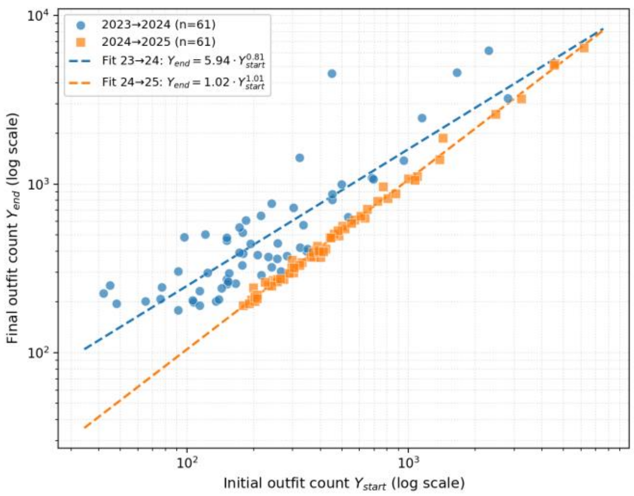

Figure 7 – Initial outfit stock vs. end-of-window outfit stock (log-log scale, balanced panel of n = 61 avatars present in all three snapshots)

5. DISCUSSION

We first discuss the relationship between avatar and outfit creators (the right-hand side of Fig. 3).

The principal finding of this study is a divergence between static and dynamic descriptors of cross-creator allocation. On the static side, despite the market size more than tripling from 2023 to 2025 [41], there was no statistically significant change in the HHI; the cross-creator distribution of compatible outfit allocations remains in the "unconcentrated" range under standard merger guideline thresholds [42]. Taken in isolation, this would suggest that the canonical "network-effects-imply-concentration" trajectory does not characterize allocation behavior in the VRChat avatar market over this window, contrasting with the general view in industrial organization theory that markets with strong network effects are "typically concentrated" [23]. On the dynamic side, however, the avatar-level power-law regression detected a statistically significant change in growth elasticity between the two windows ($\Delta\gamma = 0.20$, paired bootstrap 95% CI [0.06, 0.35], p = 0.003; Table 3), with point estimates rising from $\gamma = 0.81$ in 2023–2024 to $\gamma = 1.01$ in 2024–2025. The 2023–2024 elasticity lies significantly below 1, indicating a clearly sublinear regime in which smaller stock avatars were closing the gap with incumbents; the 2024–2025 elasticity is essentially equal to the proportional-growth threshold, and the shift between windows is statistically distinguishable from zero at the 1% level. The two descriptors thus point in different directions: a snapshot view sees the cross-creator distribution as competitive and stable, while a growth-dynamics view detects an emerging shift away from sublinear catch-up at the avatar level. The latter constitutes a latent trajectory toward future concentration that standard static descriptors do not capture, and is the central object of the policy discussion that follows.

5.1 Countervailing forces against concentration

The UGC metaverse network effects framework presented in this paper (Fig. 3) illustrates a reinforcing loop in which (1) a popular avatar attracts (2) a supply of outfits, which (3) broadens customization options and thereby (4) further raises the avatar's subjective value. If this mechanism acted in isolation, we would normally expect the HHI to rise over time, reflecting a growing concentration of demand around a handful of leading avatars.

However, the empirical evidence shows that the HHI has remained around 800 from 2023 to 2025, a range classified as "unconcentrated" under standard competition guidelines [42].

In such a state, factors represented in our hypothetical model of avatar utility (as defined in Section 3.4) could plausibly inhibit large-scale shifts in the market share. Specifically, high switching costs (λc_{ij}) and established creator brand power ($\zeta g(k_j)$) likely generate strong lock-in effects. Furthermore, the market is characterized by strong horizontal product differentiation, where an avatar's baseline appeal (α_j) and users' idiosyncratic preferences (ε_{ij}) play a crucial role. This differentiation makes it structurally difficult for a single avatar style to dominate the market, thereby contributing to the stable HHI [16, 31, 43]. While our analysis cannot measure these factors directly, the stability of the top avatar creators' shares lends exploratory support to this multifaceted explanation.

Prior research also suggests that when factors like product differentiation, multi-homing, and partial compatibility coexist with strong network effects, a multi-platform equilibrium can emerge, stabilizing concentration at a moderate level [43, 44]. [43] argue that even in markets with strong network effects and switching costs, competition can be sustained by countervailing forces such as strong product differentiation and multi-homing by complementors. Our findings suggest these exact mechanisms are at play in the UGC avatar market. First, avatars are subject to intense horizontal product differentiation, rooted in diverse user aesthetic preferences for countless styles ranging from "kawaii" to mech. This fragmentation of demand structurally prevents any single creator's style from dominating the entire market. Second, from the perspective of outfit creators (the complementors), multi-homing is prevalent. While adapting an outfit for a different avatar incurs some time cost, it does not require recreating it from scratch, making it feasible for creators to support multiple popular avatars simultaneously. This practice of "multi-homing" across multiple avatar ecosystems is common and mitigates the risk of a single avatar platform achieving exclusive control over complements.

These factors combined help explain why the market sustains a moderately concentrated, multi-platform equilibrium, as observed in our stable HHI findings, rather than succumbing to a winner-take-all outcome.

Indeed, in the video game console market, three major hardware platforms coexisted despite strong indirect network effects with complementary game software [45]. In the avatar market, although outfit creators incur some time cost to adapt an outfit for a different avatar, they do not need to recreate it from scratch. Therefore, the market concentration may have hit a ceiling around HHI ≈ 800 [46, 47].

Furthermore, avatars are products deeply rooted in users' aesthetic preferences, leading to highly diverse and fragmented demand (horizontal product differentiation). It is structurally difficult for a single avatar (or the style of a specific avatar creator) to dominate the entire demand, allowing for the existence of various niche markets. This point is consistent with the argument by [43] that product differentiation can be a factor that sustains competition even in markets with switching costs and network effects.

Related theoretical perspectives reinforce this view. [48] indicates that even in a market with strong network effects, building unique positions can avert a single-player monopoly and foster an environment where multiple players coexist. Moreover, [49] points out that when a variety of user segments exhibit distinct preferences, and a single platform (or, in this context, a single avatar) cannot profitably cater to all segments, the market is likely to be served by multiple competitors. Even if the range of customization for a given avatar is narrow because few outfits are supported, users will choose avatars based on their individual preferences, a scenario captured by the ε_{ij} term in the hypothetical model.

5.2 Cumulative advantage

However, the change in growth elasticity detected by the power-law regression, significant at the 1% level under our primary specification, suggests that this "stable equilibrium" is not static and may be shifting toward a dynamic concentration process. The point estimate of γ has moved from 0.81 in 2023–2024 to 1.01 in 2024–2025, reaching the proportional-growth threshold. This transition can be interpreted through our utility model as a change in the relative importance of its components. As the market matured, the effect of outfit variety (xj) on an avatar's utility, captured by the coefficient β, may have become synergistic rather than merely additive. Concurrently, the brand power of leading creators $(\zeta g(kj))$ could be amplifying expectations for future outfit development, attracting a disproportionate share of new outfit creation and thus accelerating their growth. This suggests that the market may be crossing a tipping point where cumulative advantage begins to overpower the stabilizing forces of product differentiation (Fig. 7). Whether this represents a transient redistribution or the early stage of a longer-term tightening is not resolvable with the data at hand; we return to this in Section 5.4.

The indirect network effects discussed in this paper constitute a hypothesized mechanism through which the content value of avatars may be endogenously enhanced. Specifically, when an avatar gains popularity, third-party creators may be incentivized to produce and sell compatible outfits, increasing the supply of complementary goods. Under the indirect network effects mechanism, this is hypothesized to improve the avatar's perceived content value. The hypothesized value-creation loop has implications for each stakeholder. For avatar creators, their work could become a hub in the ecosystem, providing an incentive to enhance their own creation's value by leveraging the creativity of others. For outfit creators, there is the appeal of accessing a larger potential audience by targeting popular avatars. From the perspective of the platform operator (e.g., VRChat), such a creator-led value loop is hypothesized to enhance platform appeal without the operator bearing the costs of content development, although our data captures only the within-platform avatar outfit market and does not directly measure platform-level user dynamics (see Section 3.2).

5.3 Policy implications

The policy implications of our analysis follow from the divergence we document between static and dynamic descriptors of cross-creator allocation. We separate what is directly supported by the data from what is forward-looking, in order to scope each claim appropriately.

Directly supported by the analysis. The HHI for cross-creator outfit allocation in the VRChat avatar market remains in the unconcentrated range under standard merger-guideline thresholds [42] across all three snapshots. Concurrently, the cross-sectional growth elasticity of incumbent stock has shifted between consecutive snapshot pairs, with the change Δγ statistically distinguishable from zero in our primary specification (Table 3). The single most direct policy implication of these two findings is methodological: competition assessment of UGC metaverse markets, and arguably of platform-adjacent digital goods markets more broadly, should not rely on static concentration metrics alone. A market that registers as competitive on the HHI can simultaneously exhibit a growth-elasticity profile consistent with the early stages of cumulative advantage in creator allocation. Pairing static with dynamic diagnostics is therefore advisable for policy bodies engaged in monitoring such markets, including the ITU FG-MV [14] and ISO/TC 324.

Forward-looking and conditional. Beyond this directly supported implication, our findings raise but do not resolve several questions for which our data do not provide direct evidence. We list these as conjectures rather than conclusions.

First, if the elasticity continues to rise into a superlinear regime, the cross-creator distribution of compatible outfits could move toward measurable concentration on standard static metrics in subsequent observation windows. Whether this in fact occurs is an empirical question for follow on data collection, not a finding of this paper.

Second, the structural feature that many avatar creators are individuals or very small enterprises may make the market susceptible to acquisition or contractual capture by larger entities. A capital-intensive entity could, at a modest cost relative to platform revenues, seek exclusive agreements with leading creators and shift the cross-creator distribution toward concentration ex post. Whether such acquisitions are occurring, and whether they would in practice tighten cross-creator concentration, is beyond what our data can address. Counterforces driven by community dynamics, including fan communities, SNS-based creator reputations, and the value creators derive from independence, may equally well constrain such strategies. We flag this scenario as one to which regulatory authorities concerned with platform-adjacent markets may wish to remain attentive, but we do not present it as a finding.

Third, the question of whether interoperability standards such as VRM [50] reduce switching costs and thereby alter the trajectory of allocation behavior is methodologically tractable but requires comparative data we did not collect. Section 5.4 returns to this as a direction for future research.

Scope of the policy implications. All implications above derive from a single UGC metaverse satisfying conditions (i) through (iii) of Section 1, observed over a 24-month window through a single e-commerce site (BOOTH). Generalization to other UGC metaverses, to platform-internal metaverses such as Fortnite and Roblox, or to non-metaverse digital-goods markets, would require additional empirical work.

5.4 Limitations and future research

We must acknowledge several limitations of this study, which in turn suggest avenues for future research.

First, our empirical analysis is restricted to a single platform, VRChat, and to transactions on a single e-commerce site, BOOTH. While VRChat is currently the leading exemplar of a UGC metaverse as defined in Section 1, the dynamics we document may not generalize to platforms with different operational models. Platforms such as Fortnite and Roblox lie outside the structural conditions of our definition, and the mechanisms of indirect network effects and switching-cost lock-in we analyze are not directly transferable to such cases. Second Life satisfies condition (i) of our definition but operates an internal marketplace economy that differs structurally from VRChat's reliance on external e-commerce; comparative analysis with Second Life therefore remains an important direction for future research, as does contrasting analysis with platform-internal metaverses. Our findings should accordingly be read as documenting the dynamics of a UGC metaverse satisfying conditions (i)–(iii), not as a general claim about metaverse markets as a whole.

Second, the two windows differ in length ($T_1 \approx 1.61$ years for 2023→2024 and $T_2 \approx 0.42$ years for 2024→2025), and the elasticity γ in equation (3) is estimated over the entire window without explicit time normalization. To assess whether the observed shift in γ is robust to this asymmetry, we consider a multiplicative updating process in which the per-period elasticity $\dot{\gamma}$ is constant within each window. Under this process, repeated application over a window of length T yields a window-level elasticity $\gamma \approx \dot{\gamma}^{T}$, so that $\dot{\gamma} = \gamma^{\frac{1}{T}}$ provides an annualized counterpart to γ. Applying this transformation, $\dot{\gamma}_{23\to24} = 0.88$ (95% CI [0.77, 0.97]) and $\dot{\gamma}_{24\to25} = 1.02$ (95% CI [0.97, 1.07]); the difference $\Delta\dot{\gamma} = 0.14$ remains statistically distinguishable from zero (95% CI [0.06, 0.25], $p = 0.001$), confirming the direction of the regime shift, although the magnitude is smaller relative to the unnormalized estimate. The much tighter confidence interval for $\gamma_{(24\to25)}$ than for $\gamma_{(23\to24)}$ partly reflects this same asymmetry: because incumbent stocks changed little over the short second window, Y_{end} stayed close to Y_{start}, pulling the estimated elasticity toward 1 and narrowing its interval. Equally-spaced snapshots in follow-on data collection would allow more direct comparison.

Third, our analysis uses the number of compatible outfits as the observable measure of cross-creator allocation, leaving other components of the multi-component utility framework unmeasured. Future work is needed to disentangle and measure the distinct effects of each component. For instance:

- The baseline appeal (α_j) and creator brand power ($\zeta g(k_j)$) could be operationalized using data on initial sales, social media follower counts, or community engagement metrics.
- Switching costs (λc_{ij}) could be quantified through user surveys or, if accessible, panel data analysis of individual purchasing histories to observe behavior when switching between avatars, though obtaining such granular, user-level purchasing data often presents a significant challenge as it is proprietary to platform operators.
- The impact of compatibility standards ($\eta f(s_j)$) could be assessed via a comparative study of avatars that do and do not adopt standards like VRM [50].

Addressing these aspects will allow the research community to build upon the conceptual framework and exploratory findings presented here, leading to a more comprehensive understanding of competition in the UGC metaverse.

6. CONCLUSION

This paper, as an exploratory study, presented the market structure of a UGC metaverse, then focused on the associated avatar market to examine, from the perspective of electronic commerce policy, how the indirect network effects arising from the complementary relationship between avatars and outfits impact the market structure. The analysis yielded the following major findings:

First, this paper proposes a conceptual framework, the UGC metaverse network effects framework (Fig. 3), in which the "avatar × outfit" pair functions as a complementary-goods system layered onto direct user-base network effects. This framework parallels the general "hardware × software" model but is structurally looser, because avatars retain standalone utility for self-expression even without supplementary outfits. The framework is offered as a hypothesis whose central observable implication, that incumbent outfit stock should translate into accelerating subsequent growth if indirect network effects operate in the conjectured direction, is what we then examine empirically.

Second, the statistical analysis using market data from 2023 to 2025 shows that, even though the overall market scale expanded rapidly, the top-tier share of compatible outfits remained stable, while mid- to lower-tier creators experienced partial turnover. The HHI remained in the unconcentrated range under standard merger guideline thresholds [42]. Taken at face value, this static picture is consistent with existing theories [16, 31] that markets with network effects can reach stable equilibria where major short-term shifts in share distribution are unlikely.

Third, the avatar-level power-law regression quantified the temporal change in growth elasticity. In the balanced panel of avatars present in the top 100 ranked set across all three snapshots ($n = 61$), the point estimate of γ rose from 0.81 in 2023–2024 to 1.01 in 2024–2025, a shift of +0.20 with paired bootstrap 95% CI [0.06, 0.35] and two-sided $p = 0.003$, statistically distinguishable from zero at the 1% level. The 2023–2024 elasticity lies significantly below 1, confirming a sublinear regime in which mid-tier avatars closed the gap with incumbents; the 2024–2025 elasticity is essentially equal to the proportional-growth threshold, and the change between windows is significant. This shift indicates the cessation of sublinear catch-up at the avatar level, providing new evidence that, despite the stability of the current HHI, there is a latent trajectory toward future concentration.

In summary, due to the interplay between 3D avatars and their outfits as complementary goods, the theoretical likelihood of pronounced indirect network effects and lock-in suggests that short-term share distributions may be prone to entrenchment. Nonetheless, the empirical market analysis confirms that certain levels of competition persist, attributable to the differentiation strategies of multiple creators and users' distinct preferences. However, given the statistically-significant rise in growth elasticity from sublinear toward proportional, the catch-up dynamic that previously compressed the cross-avatar distribution has weakened. If this new regime persists, the cross-avatar distribution would no longer compress, and any further rise in elasticity into the superlinear range could cause static concentration metrics such as the HHI to begin rising in subsequent observation windows.

As of 2025, public discourse frequently characterizes the metaverse as a sector that has passed its period of intense investor and media attention. The continued growth of the VRChat avatar market observed in this study, alongside the change in growth elasticity detected in our analysis, suggests that the UGC metaverse remains a live market warranting both academic and regulatory attention. For platform researchers, these empirical patterns, namely a stable HHI coexisting with a shift in avatar-level growth elasticity from clearly sublinear to proportional, provide a reference point against which other UGC-driven digital goods markets can be assessed. Future longitudinal data, additional snapshots, and comparative analyses across UGC metaverses, notably Second Life and emerging platforms satisfying conditions (i) through (iii) of Section 1, will be needed to determine whether the divergence we document is specific to VRChat or characteristic of UGC Metaverses more broadly.

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Figures 1 and 2, as well as the overview of digital goods circulation in the metaverse presented in Section 1, are based on and adapted from the author's prior work [55], in which the author developed an earlier formulation of the avatar outfit market structure for an analysis focused on a single-time-point cross-section. The present paper extends that line of inquiry by adding a longitudinal market analysis (2023–2025), the UGC metaverse network effects framework, and the power-law growth-elasticity diagnostic, none of which appears in [55].

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

This manuscript was initially composed in Japanese, and ChatGPT was used as an auxiliary tool during the English translation process. Moreover, ChatGPT was utilized to review the Python code for figure creation. In the interest of transparency, I acknowledge this usage here.

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