ASRJETS
American Academic Scientific Research Journal for Engineering, Technology, and Sciences
Peer-Reviewed International Journal
ISSN (Print): 2313-4410 | ISSN (Online): 2313-4402
https://asrjetsjournal.org

Content Accumulation, Audience Concentration, and Connective Selectivity on Instagram: A Population-Level Study of NBA Teams

Maximilian Mfaume[a]
a: University of Dar es Salaam Business School, Tanzania
Email: mfaumejr7@gmail.com

Accepted: 22/09/2026 | Published: 22/10/2026

Abstract

Three numbers sit at the top of every Instagram profile, and on a National Basketball Association (NBA) team's account they are often read as one verdict on how well the team is doing online. They are not the same kind of number. The post count is an archive the club has built and pruned over years, the follower count is the outcome of other people's choices, and the following count is a decision the club made itself about whom to subscribe to. This study asks how far the three actually move together, using the official Instagram accounts of all 30 NBA teams as a complete population captured between 31 August and 2 September 2026, after the 2025-2026 season. Each profile was captured as screenshots, the author transcribed the displayed counters by hand and checked them against an Optical Character Recognition (OCR) pass, and Instagram's abbreviated thousand (K) and million (M) values, which the platform shows at varying precision, were converted to approximate numbers. Medians, concentration ratios, a Gini coefficient with a Lorenz curve, and Spearman rank correlations describe the population without any sampling inference. The 30 accounts together displayed approximately 184.9 million followers (median 4.5 million); the two largest accounts held about 30.3 percent of that total and the five largest about 48.6 percent, and the follower Gini coefficient was 0.445, while post stocks were far more even (Gini 0.125; median 19,650). Posts and followers were only weakly rank-associated (Spearman rho = 0.277), and accounts followed had weak negative rank associations with followers (rho = -0.158) and with posts (rho = -0.094). Within a single league, then, content accumulation, audience scale, and connective selectivity vary independently enough that the study treats them as separate dimensions of what it calls platformed organizational visibility. Because the data are one snapshot of rounded public counters, they support no claim about growth, engagement, or causation.

Keywords: Instagram; NBA teams; organizational visibility; audience concentration; digital-trace research; sport marketing; platform metrics

1. Introduction

1.1. Research background

Open any National Basketball Association (NBA) team's Instagram profile and, before a single post appears, the header reports how many posts the account holds, how many accounts follow it, and how many it follows. The team controls none of this presentation. Instagram decides that these figures are shown, where they sit, and how the larger ones are rounded, and because the layout is identical on every profile the numbers lend themselves to league tables. Comparing them has become an ordinary way of judging which sport organizations are doing well online, at a time when official accounts on the major platforms are a routine part of brand management and Instagram is one of the principal channels through which teams present themselves visually to dispersed audiences [1, 2].

The trouble is that a league table built from these numbers compares unlike things. A post count is a stock that grows over the life of the account and falls only when posts are removed, so it says what has been kept and nothing about what is being done now. A follower count is the sum of other people's

decisions to subscribe, frozen at the moment of viewing. A following count is a choice the team made itself. Ranking all three as if they were readings on one scale of digital performance treats an archive, an audience, and an editorial decision as measures of the same quality. Earlier work has already warned against reading follower counts as influence or performance [3, 4]; the same caution is applied here to all three counters, each treated as a dimension of its own.

1.2. Research problem

Much commentary on team social media, and some research, nonetheless reads the three figures as steps on one ladder. A large post count is offered as the reason for a large audience, a club that follows almost nobody is said to be projecting prestige, and a club that follows thousands is said to be engaging its community. Each reading is plausible, and each depends on an assumption that is seldom examined, that the counters are interchangeable measures of one quality. If different processes produce them, a very large audience can sit beside a modest post stock, and a tiny following count beside a small audience, without any contradiction. Whether the counters actually line up has rarely been checked against a complete set of comparable organizations.

The counters themselves raise a further difficulty. Instagram rounds the larger values into thousand (K) and million (M) notation, and the rounding coarsens with magnitude, so a header reading 31.5M is a display value with three significant digits, not an exact tally. Nor do the counters say anything about reach, impressions, engagement, or whether the followers are genuine accounts [3]. Any analysis that starts from them has to be explicit about what they can support. Here they are taken as what they are on the screen, platform-generated markers of position that shape how organizations are seen and compared. The question is how those markers are distributed across one bounded population and how far they move together.

1.3. Research gap

Research on sport organizations and social media has concentrated on the content teams post, the brand attributes that content communicates, and the interactions it generates [1, 5, 6]. Work on audience size has mainly studied athletes, modeling follower growth around events such as the draft [7]. Network studies of sport organizations have asked who is central in an organization's follower network on Twitter [8, 9]. A population-level examination of the profile counters themselves, one that treats content stock, audience scale, and outgoing connectivity as separate dimensions and measures their alignment instead of assuming it, has not been carried out. The more important gap is conceptual: organizational social-media research has not established whether indicators that platforms make commensurable behave as a single construct.

The 30 NBA teams offer a bounded setting in which to ask. One league on one platform removes variation attributable to sport, league membership, and platform architecture, while leaving franchise-level differences uncontrolled. Franchise history, market size, championship success, globally prominent players, account-management resources, communication strategy, archiving or deletion practices, and organizational priorities all vary across the 30 teams, and none of them is observed in the dataset. If heterogeneous configurations persist even within a shared league and platform environment, the case for treating the indicators as distinct dimensions becomes stronger, although the reasons for any franchise's position remain unexplained.

1.4. Research questions and contribution

Four research questions follow. Research Question 1 (RQ1) asks how accumulated posts, followers, and accounts followed are distributed across the official Instagram profiles of NBA teams. Research Question 2 (RQ2) asks to what extent content accumulation, audience scale, and outgoing

connectivity are associated across those profiles. Research Question 3 (RQ3) asks how concentrated visible Instagram audience scale is among NBA teams. Research Question 4 (RQ4) asks what contrasting visibility configurations emerge from differences in content accumulation, audience scale, and connective selectivity. No hypotheses are proposed, because the literature reviewed below offers no defensible directional prediction about how the three indicators should align, and the design is a cross-sectional description of a complete population.

The value of the analysis lies in testing an assumption that usually goes unstated: that counters a platform places side by side can be read as one measure. Once posts, followers, and accounts followed are treated as separate dimensions of platformed organizational visibility, that assumption becomes something the evidence can confirm or contradict. The verified figures for the complete NBA team population show how the dimensions are distributed, concentrated, and associated at a documented capture window, and the procedure for handling abbreviated public counters, which keeps displayed and converted values apart and holds interpretation within what a single snapshot can support, is set out in enough detail to be repeated.

2. Literature review

2.1. Platformed organizational visibility

What an organization reveals and what it hides was never a simple matter, but digital platforms changed the terms. Treem and Leonardi placed visibility among the affordances of social media, together with persistence, editability, and association, through which behaviors that used to be private or fleeting become observable [10]. Leonardi and Treem then argued for behavioral visibility as a paradigm for organization studies, on the ground that digitization and datafication set the conduct of people and collectives before third parties in standardized, comparable form [11]. Flyverbom and colleagues drew the organizational consequence: managing visibilities becomes a task in itself, because organizations display and conceal at the same time and what an observer sees depends on the affordances of the technology through which the seeing happens [12].

The technology that makes conduct visible also shapes what is seen. Gillespie's analysis of the word platform showed how it presents intermediaries as open and even-handed while they are shaping what becomes visible [13]. Van Dijck and Poell read this as a social-media logic of programmability, popularity, connectivity, and datafication, in which popularity is manufactured by mechanisms that make some actors more visible than others [14]. The same point holds from the participant's side: on Facebook, visibility is algorithmically constructed and users fear invisibility more than exposure [15], and Instagram influencers treat the platform's opaque rules as a game to be played [16]. What an organization's profile shows, then, is a joint product of the organization's conduct and the platform's architecture. That joint production is what makes visibility platformed.

2.2. Public platform metrics and commensuration

The counters in a profile header are a small but exact case of quantification and commensuration. Espeland and Stevens defined quantification as the production and communication of numbers and commensuration as the transformation of different qualities into a common metric [17, 18]. What makes commensuration consequential is that it creates comparisons where none existed, and comparison changes how the compared things are judged. An Instagram header does exactly this on every load, placing three counters that arise from different processes in one row, at one visual weight, rounded by one magnitude-dependent rule. Gerlitz and Helmond traced the wider system in which such counters operate, a like economy where buttons and counters convert user activity into numbers that circulate as signals of value and serve as the currency of the social web [19].

Such numbers reveal less than they promise. Baym reviewed social-media metrics and concluded that visible counts are fallible and ambiguous measures of audience, shaped by the values of the people who build and read them [3]. Cha and colleagues found on Twitter that a large follower total said little about influence measured through retweets and mentions, which they called the million follower fallacy [4]. Marwick showed how Instagram fame organizes itself around visible follower counts and the imitation of celebrity imagery, so that follower scale works as a status signal whose meaning is socially made [20]. If a single counter cannot be read as engagement, reach, or influence, then the three counters should not be folded into one measure either, and that is why they are analyzed separately here.

2.3. Instagram and professional sport organizations

Sport management research on social media has grown substantially since Filo, Lock, and Karg reviewed the field and identified relationship marketing and service-dominant logic as its dominant frames [2]. Parganas, Anagnostopoulos, and Chadwick examined how a professional football organization used Twitter to communicate product-related and non-product-related brand attributes and how followers responded through the platform's interaction features [5]. Anagnostopoulos and colleagues carried the same question to Instagram, analyzing photographs posted by two English Premier League clubs and finding that product-related attributes dominated and drew greater interaction [1]. Maderer, Parganas, and Anagnostopoulos compared Facebook and Twitter communication by ten valuable European football clubs across in-season and off-season periods and found that posting frequency rose during the season [6].

Basketball organizations have received less attention. Opelík and colleagues evaluated the Instagram communication of professional clubs in the Czech National Basketball League and found that clubs in the same league were not at the same level in their use of the platform [21]. Naraine and Parent used ego-network analysis of Twitter followership to identify centralized users around two national sport organizations [8], and Naraine segmented the follower networks of four professional teams in Toronto, including an NBA franchise, into interest-based groups [9]. Su and colleagues modeled changes in the social-media followings of athletes around the NFL Draft and showed that league and team brands shape athlete follower growth [7]. None of these studies examined how profile-level counters align across a complete league population, and none treated the following count as an organizational choice worth analyzing in its own right.

2.4. Cumulative advantage and concentrated digital audiences

The unequal distribution of attention is a long-standing theme in the sociology of science and culture. Merton described the Matthew effect, in which already eminent scientists receive disproportionate credit and visibility, and he noted its consequences for the communication system of science as well as for its reward system [22]. DiPrete and Eirich reviewed cumulative advantage as a general mechanism of inequality in which a favorable relative position becomes a resource that produces further relative gains, and they distinguished several formal versions of the mechanism [23]. Salganik, Dodds, and Watts demonstrated experimentally that social influence in an artificial cultural market increased both the inequality and the unpredictability of success [24].

Concentration of attention is now treated as a structural feature of the digital economy. In Hindman's account the internet concentrates audiences instead of dispersing them because small early advantages in stickiness and infrastructure compound over time [25], and Webster describes a marketplace of attention that is diverse and concentrated at once, its audiences overlapping heavily across a few dominant outlets [26]. Both accounts help make sense of a skewed follower distribution among sport organizations. Neither, however, can be invoked to say that cumulative advantage has

been observed, because that claim requires growth measured over time. Cumulative advantage is used in this article to interpret the shape of the follower distribution, and only for that.

2.5. Conceptual gap

Whether the counters a platform standardizes behave as one dimension of organizational digital success or as several has not been examined in the work reviewed above. Visibility on a platform is a joint product of organizational conduct and platform architecture. Public counters commensurate unlike qualities and are unreliable as measures of influence or engagement, and digital audiences tend to concentrate. The sport-management studies examined content, interaction, or follower growth, and the joint distribution of content stock, audience scale, and outgoing connectivity across a complete set of comparable organizations did not arise in any of them.

3. Theoretical Foundations and Conceptual Framework

The theoretical material does different work at different points in the argument. Affordance and behavioral-visibility research answers the prior question of why organizational traces are observable to outsiders at all. Commensuration theory answers why standardized counters invite comparison across quantities that record different processes, and it defines the central theoretical problem. Cumulative-advantage research and the attention-economy literature enter only at the interpretive stage, to make sense of the concentration of displayed follower scale. Table 1 sets out the function, observed construct, and inference boundary for each.

Table 1. Theoretical foundations, their function in the manuscript, the observed construct to which each applies, and the boundary of the inference each supports

Theoretical foundation	Function in the manuscript	Observed construct	Boundary of inference
Social-media affordances and behavioral visibility (Treem and Leonardi; Leonardi and Treem)	Explains why retained posts, displayed followers, and outgoing subscriptions are observable to third parties	All three profile counters	Counters are sociotechnical representations; no inference to motives, communication quality, engagement, influence, or performance
Commensuration theory (Espeland and Stevens)	Principal explanatory mechanism: shared display architecture invites comparison of differently produced quantities	Joint display of the three counters; their rank alignment (RQ2, RQ4)	Explains why counters are read as interchangeable; the three-part separation is the article's own distinction
Cumulative advantage (Merton; DiPrete and Eirich; Salganik, Dodds, and Watts)	Interprets the shape of the follower distribution	Concentration of displayed follower scale (RQ3)	Not tested; growth and path dependence unobserved; interpretive, not causal
Attention-economy literature (Hindman; Webster)	Contextualizes concentrated digital audiences	Displayed follower scale	Followers are not attention, reach, impressions, or engagement; contextual lens only

3.1. Social-media affordances and behavioral visibility

Treem and Leonardi identified visibility as an affordance of social media in organizations: the infrastructure makes actions, connections, and content available to third parties who were not party to them [10]. Leonardi and Treem extended this into behavioral visibility, the condition in which digitization and datafication render the conduct of individuals and collectives observable in standardized and comparable forms [11]. Public profile counters are a clear instance. What the post counter shows is the stock of posts the account has retained; what the follower counter shows is how many accounts subscribe; what the following counter shows is whom the organization has chosen to subscribe to. In each case the platform decided what would be counted, when it would be rounded, and where it would appear.

The visibility is partial. Nothing in a retained post stock records what was deleted, nothing in a follower count records who looks or interacts, and nothing in a following count records who was

followed or why. Yet observers read the standardized display and draw inferences from it, and those inferences, rather than the unobserved practices behind the numbers, are the subject of this analysis. The foundation licenses no claim about organizational motives, communication quality, engagement, influence, or performance, and no such claim is made.

3.2. Commensuration theory

Espeland and Stevens describe commensuration as the transformation of different qualities into a common metric, an operation that creates comparability between entities that were not previously compared and thereby changes how they are evaluated [18]. In their later work on quantification they added that numbers, once produced and communicated, acquire an authority that can detach them from the processes they summarize [17]. The Instagram profile header is a working example: retained organizational posting, audience subscription decisions, and outgoing organizational subscriptions are three different processes, and the header presents their outputs in one row under one visual hierarchy, even while rounding them at precisions that vary with magnitude.

This is where the central theoretical problem arises. Visual commensuration of counters that come from different organizational and audience practices encourages observers to treat unlike quantities as interchangeable signs of digital success. Whether the quantities really move together is the empirical question the article answers, and commensuration theory is the lens through which the answer is read. The cautions of Baym and of Cha and colleagues against reading follower counts as influence or performance [3, 4] support the same reading. The step of treating retained posts, displayed followers, and accounts followed as three analytical dimensions is the article's own.

3.3. Cumulative advantage

Cumulative advantage enters through two strands. Merton's Matthew effect and the review by DiPrete and Eirich describe how a favorable relative position becomes a resource for further relative gains [22, 23]; Salganik, Dodds, and Watts showed experimentally that social influence raises both the inequality and the unpredictability of success [24]. These works are used here for a single purpose, to help interpret the shape of the observed distribution of displayed follower scale. No test of the mechanism was possible. Growth and path dependence were not observed, and one cross-sectional snapshot gives no way to show that earlier advantage produced later advantage. The theory therefore offers an interpretive explanation for concentration, not a demonstrated causal mechanism.

3.4. Attention-economy literature

Hindman argued that the digital economy concentrates audiences because small early advantages in infrastructure and stickiness compound, and Webster described a marketplace of attention in which public attention is at once diverse and concentrated across a small number of dominant outlets [25, 26]. On this reading, concentrated digital audiences are an expected pattern, and the literature serves as a contextual lens for the results on displayed follower scale. It is not used to claim that attention was measured. A follower count records a standing subscription and says nothing about reach, impressions, viewing, interaction, engagement, or active attention, so the results are framed in terms of displayed audience scale and its concentration.

3.5. Platformed organizational visibility as an integrative framework

Platformed organizational visibility is the integrative conceptual framework developed for this article; it is not a previously validated theory. It refers to the publicly observable position of an organization produced through platform-standardized indicators: public because any visitor can see it, observable because it is displayed as a number, and platform-standardized because the platform decides which indicators appear, in what format, and with what abbreviation. Figure 1 lays the four

foundations out as one chain. At the top, platform infrastructure produces the standardized public counters. Those counters make organizational traces visible to outsiders, who draw inferences from them. Because the display architecture is shared, indicators that were produced differently are made comparable, and it is at this point that content accumulation, audience scale, and outgoing connectivity can come apart into distinct configurations. Displayed audience scale, one of the three, is in addition unequally distributed across the population. The framework's job is to organize and interpret that pattern by keeping the production processes behind the three counters apart. It predicts nothing and explains nothing causally.

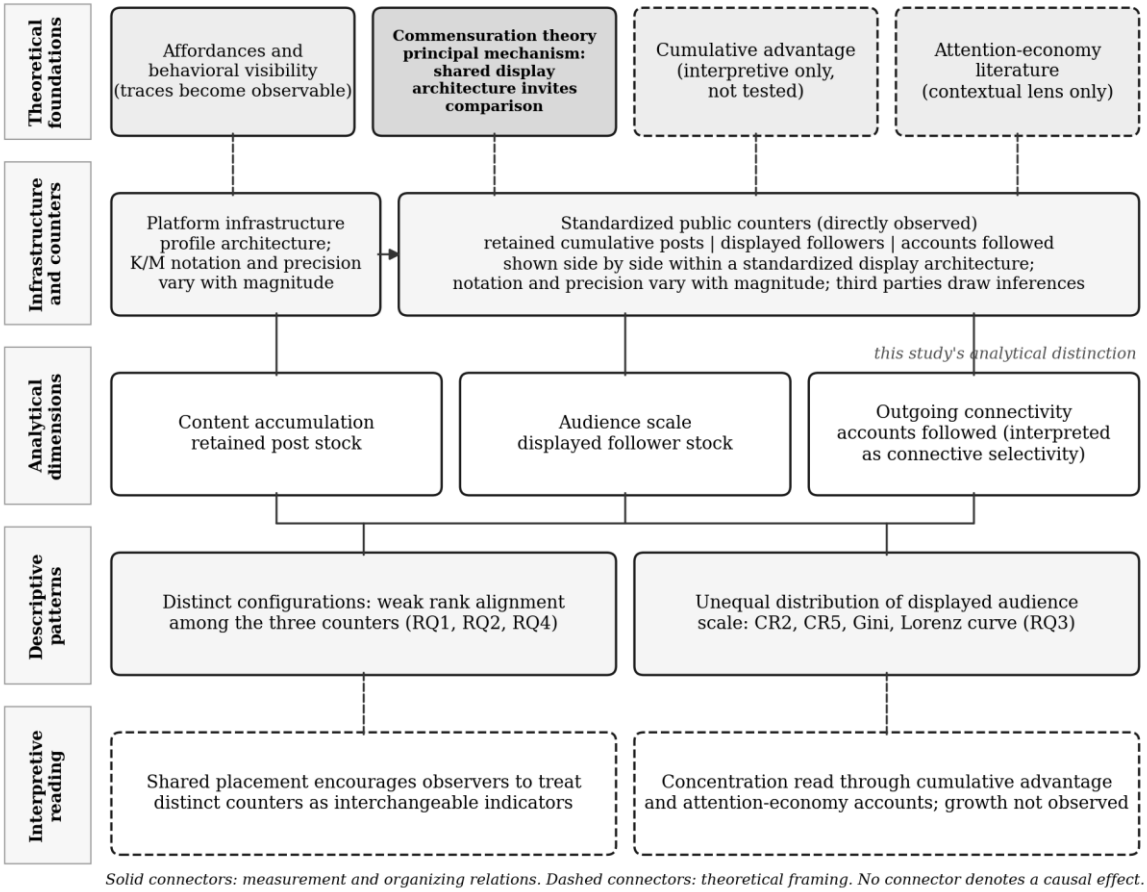


Figure 1. Integrative framework of platformed organizational visibility, distinguishing theoretical foundations, observed counters, analytical dimensions, descriptive population patterns, and interpretive mechanisms that were not tested (connectors denote organizing relations, not causal effects)

Table 2 defines the three dimensions with their operational measures and limits. Content accumulation is the visible stock of posts an account has retained. Publishing a post raises the counter and deleting or archiving one lowers it, so the displayed figure is a net stock and not a record of everything ever posted. The age of the account, the way it has been used, and what has been removed all feed into the number, and none of them can be recovered from it. Being cumulative, the figure carries no information about posting frequency in any season and is not read as current activity. Its analytical use is to index the size of the retained archive to which an audience is attached.

Audience scale is the number of followers displayed at the capture window. It differs from the post stock in origin, since it results from decisions taken by other accounts, and it is the counter most commonly read as success. For larger accounts Instagram shows it in rounded form at varying precision. The number says nothing about whether those followers look at the content, interact with it, are active, or are genuine. Audience concentration is a population-level property derived from audience scale. It is the degree to which the combined displayed followers of the population are held

by a small number of accounts, measured with concentration ratios, the Gini coefficient, and the Lorenz curve. It is interpreted in light of cumulative advantage without claiming that the mechanism was observed.

Outgoing connectivity is directly measured as the displayed number of accounts followed. Connective selectivity is the analytical interpretation placed on that count: a smaller count indicates a more restricted set of outgoing subscriptions at the capture window. The interpretation is the author's own, and it does not reveal the identities of the followed accounts, the decision process behind them, reciprocity, network centrality, or a formal organizational policy. Howison and colleagues' validity cautions for digital-trace network measures explain why the count should not be equated with network centrality [27]; they do not themselves establish selectivity as a validated construct. The value of the dimension is that it records an outgoing organizational choice rather than an audience decision or a retained post stock, which makes it analytically distinct from the other two counters.

A visibility configuration is the joint position of an account on the three dimensions. Because different practices produce the dimensions, configurations may be heterogeneous: some accounts may pair large displayed audiences with modest retained post stocks, others the reverse, and the following count need not align with either. The framework's one substantive commitment is that side-by-side display produces an appearance of comparability, and that this appearance is no evidence of a shared measure. It asserts no causal relation among them.

Table 2. Constructs, operational definitions, and measurement limitations

Construct	Dimension of platformed visibility	Operational measure (Instagram profile counter)	Principal measurement limitations
Content accumulation	Retained cumulative post stock	Displayed cumulative posts, converted from K notation to an approximate numeric value	Net stock affected by deletion and archiving; does not measure posting frequency in any season; abbreviated at varying precision above 10,000
Audience scale	Audience decisions attached to the account	Displayed followers at capture, converted from M notation to an approximate numeric value	Does not measure reach, impressions, engagement, loyalty, or authenticity; abbreviated at varying precision (one to three significant digits); changes continuously
Audience concentration	Population-level distribution of audience scale	Two-team and five-team concentration ratios, Gini coefficient, Lorenz curve of displayed followers	Computed from abbreviated inputs of varying precision; describes one capture window; does not test growth or cumulative advantage
Outgoing connectivity (interpreted as connective selectivity)	Directly observed count of outgoing subscriptions; selectivity is the author's analytical interpretation	Displayed number of accounts followed, used as shown	Does not reveal identities of followed accounts, the decision process, reciprocity, network centrality, or a formal organizational policy

4. Materials and methods

4.1. Research design

This is a full-population, cross-sectional digital-trace study of publicly visible organizational Instagram indicators. Digital traces are by-products of activity on an information system, produced for the system's purposes and not for research, so their validity rests on understanding how the system generates them [27]. Venturini and colleagues put the same point as a reality check for digital methods: platform inscriptions are being repurposed, and the researcher has to separate, as far as possible, the phenomenon under study from the features of the medium in which it appears [28]. Everything that follows is descriptive: distributions, concentration, and rank associations are estimated for a complete population, and no causal identification is attempted.

4.2. Population and unit of analysis

The population is the official Instagram accounts of all 30 NBA teams, 15 in the Eastern Conference and 15 in the Western Conference, and the unit of analysis is the official team account. Player accounts, affiliated accounts, and league accounts were left out. Since every member of the population is included, the accounts are the population itself and the results describe them directly; they are not a sample drawn from a larger universe.

4.3. Data source and capture procedure

The author captured the data manually from the Instagram mobile application between 31 August and 2 September 2026, after the 2025-2026 playing season had ended, taking three screenshots of every account. The first is the profile header, showing the account name, verification badge, post count, follower count, and following count. The second is the About this account page, showing the date the account joined Instagram and the country in which it is based. The third is the profile Quick Response (QR) card, which confirms the handle. The profile URL was recorded with the screenshots. The source document does not record which of the three dates applies to each team, so the capture window is recorded at the account level as 31 August to 2 September 2026, and the observations are described as a postseason profile snapshot of the 2025-2026 NBA team population, not as a representation of any account throughout the season. Manual capture from the public interface was the practical option because platform programming interfaces for profile data have been progressively restricted, a condition Freelon and Bruns have described for computational research on social media [29, 30].

4.4. Variable construction

Three variables came from the profile header. Displayed values were transcribed exactly as shown, including Instagram's K and M notation, and stored separately from the analytical values. Analytical values were obtained by converting K to thousands and M to millions, so that 31.5M became 31,500,000 and 18.5K became 18,500. Values displayed without a suffix, such as a following count of 1,915 or a post count of 3,669, were used as displayed. Instagram abbreviates the larger counters at a precision that varies with the value shown, generally between one and three significant digits (31.5M carries three, 1.8M two, 3M one). The converted values therefore retain only the precision available in the public display, every aggregate derived from a K or M display is approximate, and the manuscript describes such aggregates in those terms. Two further fields, the Instagram joining month and the account location, were recorded for description only and play no part in the quantitative analysis. Conference membership was taken from the source document for descriptive comparison.

4.5. Verification procedure

Verification ran in two passes. The first was visual: every screenshot was inspected and each displayed value transcribed with its image identifier. The second was an Optical Character Recognition (OCR)-assisted machine check, not a separate human replication, whose output was compared with the visual transcription. Agreement was reached for 29 of 30 accounts. The single disagreement arose because the recognition output had dropped a decimal point; re-examining the profile at magnification confirmed the transcribed value from the source image. Every value was readable and none was imputed. The resulting register records, for each team, the conference, handle, displayed and converted values for the three counters, verification status, joining month, account location, capture window, profile URL, image identifiers, and an uncertainty flag; it is reproduced in full as Table 3.

4.6. Analytical strategy

The first check was coverage, and all 30 teams appeared exactly once with unique handles. For each counter the distributional summary gives the total where it is substantively meaningful, the minimum and maximum, the median, first and third quartiles and interquartile range, the mean, the standard deviation, and sample skewness; because the follower distribution is strongly skewed, medians and interquartile ranges are the figures relied on. Each team was then ranked on each counter, ties sharing the lower rank, and the difference between post rank and follower rank was computed. Concentration was summarized by the two-team and five-team concentration ratios (the share of combined displayed followers held by the largest two and five accounts), by the Gini coefficient of followers computed with the standard formula for a finite ordered population [31], and by Lorenz curve coordinates in the cumulative-share form introduced by Lorenz [32]. Association was measured with Spearman rank correlations for the three pairs of counters. Spearman rho is the principal measure because the questions concern rank alignment across the complete population; Kendall tau and Pearson correlations of log-transformed values are reported as sensitivity measures. Since the 30 accounts are the population, the coefficients describe the observed NBA team population at the documented capture window and carry no sampling inference. A further sensitivity analysis excluded the one team whose post count is an extreme low outlier.

Configuration analysis compared standardized values, ranks, and tertile positions on the three counters. A supplementary k-means clustering of the three standardized indicators was run with 20 random initializations and its stability was assessed with the mean pairwise adjusted Rand index. The mean index was 0.23, far below the pre-specified acceptance threshold of 0.80, so clustering results are not reported and configurations are described through transparent rank and tertile comparison. Conference comparisons are reported descriptively only. All analyses were performed with a single reproducible script, and every number in the manuscript can be regenerated from the verified dataset.

4.7. Ethical considerations

The study uses publicly displayed information about organizational accounts operated by professional sport franchises. No individual user was contacted, observed, or profiled, no private information was collected, and no post-level content, comments, or user identities were recorded. The only quantities analyzed are the aggregate counters Instagram displays to any visitor, together with the joining month and country shown on the public About this account page. Only the fields needed for the research questions were retained. The capture window is reported so that the observations can be placed in time, and no claim is made about any individual follower. No formal ethical exemption is claimed; the work is offered as responsible research on public organizational information.

5. Results

5.1. Population coverage and descriptive results

All 30 teams were present under 30 unique verified handles, 15 per conference. Table 3 lists the verified profile indicators for every team and Table 4 the distributional statistics. In total the 30 accounts displayed approximately 184.9 million followers and approximately 591,000 accumulated posts, and between them they followed 11,738 accounts. The median account showed 4.5 million followers, 19,650 posts, and 315.5 accounts followed. Every account carried a verification badge. All but one were recorded as based in the United States; the exception, the Toronto Raptors account, is based in Canada. Joining months ran from January 2011 to November 2012, so each account had existed for roughly 14 to 15 years at capture.

Table 3. Verified Instagram profile indicators for all 30 NBA teams (postseason snapshot, 31 August to 2 September 2026; displayed values retained as shown, numeric values approximate where derived from K or M notation displayed at varying precision)

Team	Conf.	Handle	Posts shown	Posts (n)	Followers shown	Followers (n)	Following	Joined
Detroit Pistons	E	@detroitpistons	18.5K	18,500	1.8M	1,800,000	420	Mar. 2012
Boston Celtics	E	@celtics	19.8K	19,800	8.2M	8,200,000	290	Jan. 2011
New York Knicks	E	@nyknicks	19.3K	19,300	5.7M	5,700,000	349	Feb. 2011
Cleveland Cavaliers	E	@cavs	26.9K	26,900	15.8M	15,800,000	259	Apr. 2012
Toronto Raptors	E	@raptors	17.4K	17,400	4.1M	4,100,000	294	Jan. 2012
Atlanta Hawks	E	@atlhawks	19.5K	19,500	2.6M	2,600,000	252	Nov. 2012
Philadelphia 76ers	E	@sixers	20K	20,000	4.8M	4,800,000	212	Feb. 2012
Orlando Magic	E	@orlandomagic	18.6K	18,600	2.1M	2,100,000	457	Jul. 2012
Charlotte Hornets	E	@hornets	21.4K	21,400	2.6M	2,600,000	1,915	Mar. 2012
Miami Heat	E	@miamiheat	19.7K	19,700	6.5M	6,500,000	102	Feb. 2012
Milwaukee Bucks	E	@bucks	22.3K	22,300	5.2M	5,200,000	355	Aug. 2011
Chicago Bulls	E	@chicagobulls	14.1K	14,100	9.9M	9,900,000	392	Oct. 2011
Brooklyn Nets	E	@brooklynnets	16.2K	16,200	4.6M	4,600,000	630	Mar. 2012
Indiana Pacers	E	@pacers	26.8K	26,800	3.5M	3,500,000	414	Dec. 2011
Washington Wizards	E	@washwizards	19.1K	19,100	1.5M	1,500,000	218	Dec. 2011
Oklahoma City Thunder	W	@okcthunder	29.8K	29,800	6.1M	6,100,000	324	Jun. 2011
San Antonio Spurs	W	@spurs	24K	24,000	6.2M	6,200,000	485	Jan. 2012
Denver Nuggets	W	@nuggets	22.1K	22,100	3M	3,000,000	119	Dec. 2011
Los Angeles Lakers	W	@lakers	17.3K	17,300	24.5M	24,500,000	88	Dec. 2011
Houston Rockets	W	@houstonrockets	11K	11,000	6.1M	6,100,000	670	May 2012
Minnesota Timberwolves	W	@timberwolves	22.7K	22,700	4.4M	4,400,000	154	May 2012
Portland Trail Blazers	W	@trailblazers	22.4K	22,400	2.9M	2,900,000	624	Jan. 2012
Phoenix Suns	W	@suns	22.8K	22,800	3.5M	3,500,000	228	Jan. 2012
LA Clippers	W	@laclippers	20.8K	20,800	5.1M	5,100,000	350	Mar. 2012
Golden State Warriors	W	@warriors	23K	23,000	31.5M	31,500,000	308	Apr. 2012
New Orleans Pelicans	W	@pelicansnba	15.7K	15,700	2.6M	2,600,000	266	Dec. 2011
Dallas Mavericks	W	@dallasmavs	19.6K	19,600	4.6M	4,600,000	169	Jul. 2011
Memphis Grizzlies	W	@memgrizz	18.6K	18,600	1.9M	1,900,000	785	Mar. 2012
Sacramento Kings	W	@sacramentokings	3,669	3,669	2.2M	2,200,000	323	Feb. 2011
Utah Jazz	W	@utahjazz	18.3K	18,300	1.4M	1,400,000	286	Mar. 2012

Table 4. Distributional statistics for accumulated posts, displayed followers, and accounts followed across the 30 NBA team accounts (values derived from abbreviated public counters of varying precision are approximate)

Statistic	Posts	Followers	Following
Total	591,369	184,900,000	11,738
Minimum	3,669	1,400,000	88
First quartile	18,350	2,600,000	234
Median	19,650	4,500,000	315.5
Third quartile	22,375	6,100,000	418.5
Interquartile range	4,025	3,500,000	184.5
Maximum	29,800	31,500,000	1,915
Mean	19,712	6,163,333	391.3
Standard deviation	4,864	6,675,921	333.7
Skewness	-1.00	2.81	3.51
Gini coefficient	0.125	0.445	0.349

The three counters have very different shapes. Post stocks were tightly clustered: the interquartile range ran from 18,350 to 22,375, and 27 of 30 teams displayed between 14,100 and 26,900 posts. The distribution was negatively skewed because of one extreme low value, the Sacramento Kings account with 3,669 posts, less than a fifth of the population median; the Oklahoma City Thunder account displayed the most, 29,800. Followers were positively skewed to a much greater degree, with a mean of 6.16 million well above the median of 4.5 million and a skewness of 2.81. Following counts were

also positively skewed, driven by the Charlotte Hornets account, which followed 1,915 accounts, more than twice the next highest value; the Los Angeles Lakers account followed the fewest, 88. Conference medians were similar on all three counters. The Western Conference's larger combined follower total (approximately 106.0 million against 78.9 million) is accounted for by the two largest accounts in the league, both of which sit in that conference; it is not a general difference between conferences.

5.2. Distribution of displayed audience scale

Figure 2 plots the follower counter for every team. Two accounts stand well apart from the rest: the Golden State Warriors (31.5M) and the Los Angeles Lakers (24.5M). The Cleveland Cavaliers (15.8M) and Chicago Bulls (9.9M) form a second tier, and below the Boston Celtics (8.2M) the distribution flattens, with 20 teams displaying between 1.4 million and 6.5 million followers. Put as ratios, the largest displayed value is 22.5 times the smallest and 7.0 times the median. At the other end, the ten accounts with the fewest followers held about 11.7 percent of the combined total between them, and the fifteen smallest about 21.7 percent.

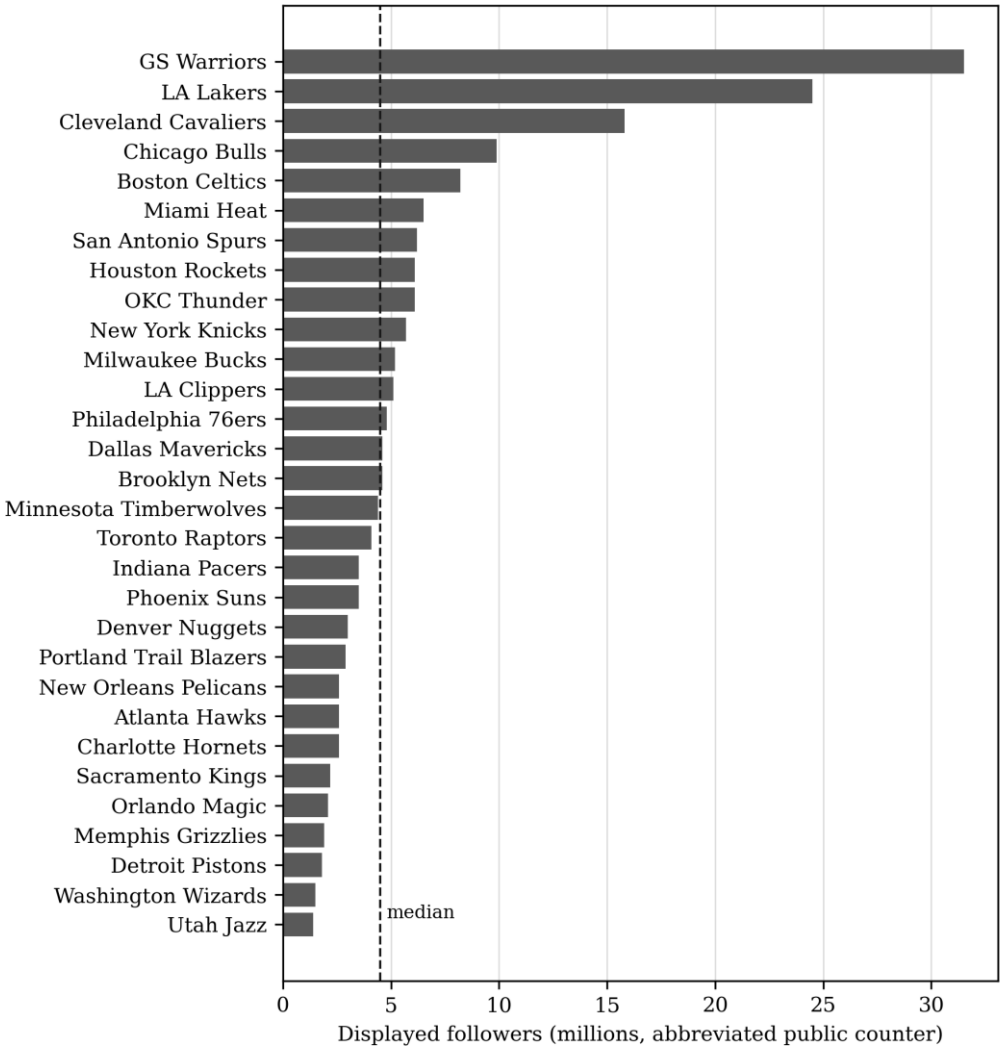


Figure 2. Distribution of displayed followers across the 30 NBA team Instagram accounts, postseason snapshot of 31 August to 2 September 2026 (values are Instagram's abbreviated public counters displayed at varying precision; dashed line marks the population median)

5.3. Concentration of displayed follower scale

The two largest accounts held approximately 30.3 percent of all displayed followers across the league, a two-team concentration ratio of 0.303. The five-team ratio was 0.486 and the ten-team ratio

0.652. The Gini coefficient of followers was 0.445; for post stocks it was 0.125 and for accounts followed 0.349, so within one population audience scale is far more concentrated than content accumulation. Figure 3 shows the same thing as a Lorenz curve, which climbs only gradually across the first 25 teams and then breaks sharply away from the line of equality where the largest five teams add nearly half the cumulative share. Each of these figures rests on abbreviated public counters and is approximate; the gaps are wide enough that the varying display precision does not alter the descriptive conclusion. About half of the combined total (48.6 percent) sits with five accounts; a sixth is needed to pass half (52.1 percent), which leaves the other 24 accounts with about 47.9 percent.

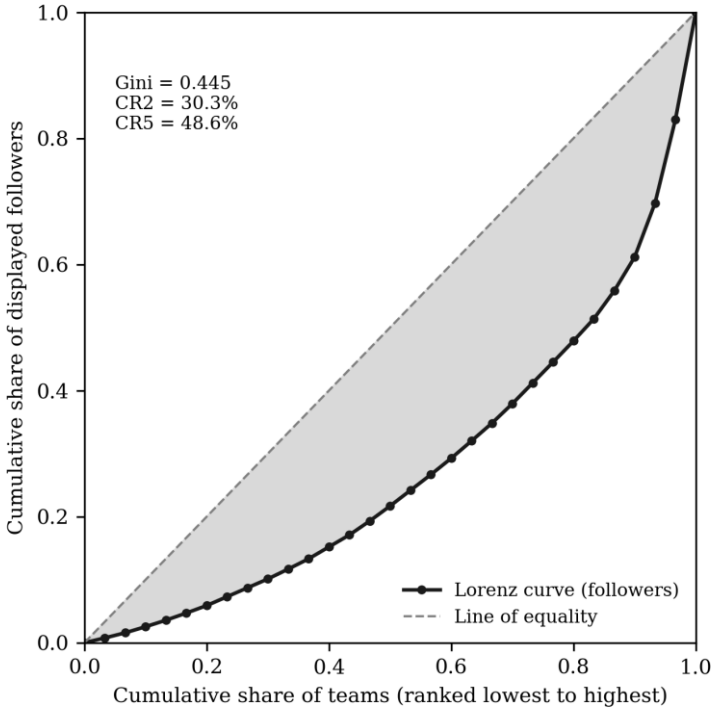


Figure 3. Lorenz curve for the concentration of displayed Instagram followers across the 30 NBA team accounts, with the Gini coefficient and two-team (CR2) and five-team (CR5) concentration ratios (computed from abbreviated public counters of varying precision)

5.4. Associations among profile indicators

Table 5 gives the association results as descriptive coefficients for the complete population. Accumulated posts and followers had a Spearman rank correlation of 0.277; the corresponding Kendall tau was 0.209, the Pearson correlation of log-transformed values 0.197, and excluding the Sacramento Kings account reduced the Spearman coefficient to 0.222. Accounts followed and followers were weakly and negatively associated (rho = -0.158; log-Pearson -0.278), and posts and accounts followed were weakly negative and close to zero (rho = -0.094). Rank order on any one counter therefore corresponds only loosely to rank order on either of the others.

Table 5. Associations among Instagram profile indicators across the 30 NBA team accounts (descriptive coefficients for the complete population; Spearman rho is the principal measure, Kendall tau and log-Pearson are sensitivity measures)

Pair of indicators	Spearman rho	Kendall tau	Pearson r (log10 values)
Posts and followers	+0.277	+0.209	+0.197
Following and followers	-0.158	-0.118	-0.278
Posts and following	-0.094	-0.055	-0.065
Posts and followers, excluding Sacramento Kings (sensitivity)	+0.222	Not applicable	Not applicable

Figure 4 plots accumulated posts against followers on a logarithmic follower axis, and the two largest audiences sit at very different positions on the post axis: the Warriors account holds the fifth-

largest post stock while the Lakers account ranks twenty-fifth. The Houston Rockets account, with 11,000 posts, displayed the same 6.1 million followers as the Thunder account, which had the largest post stock in the league. The Chicago Bulls account combined the fourth-largest audience with the third-smallest post stock. In the other direction, the Indiana Pacers and Phoenix Suns accounts held the third- and sixth-largest post stocks but only the eighteenth-ranked audience. Tertile cross-tabulation confirms the pattern. Of the ten teams in the highest post tertile, four were in the highest follower tertile, five in the middle, and one in the lowest; the ten teams in the lowest post tertile were spread three, two, and five across the follower tertiles.

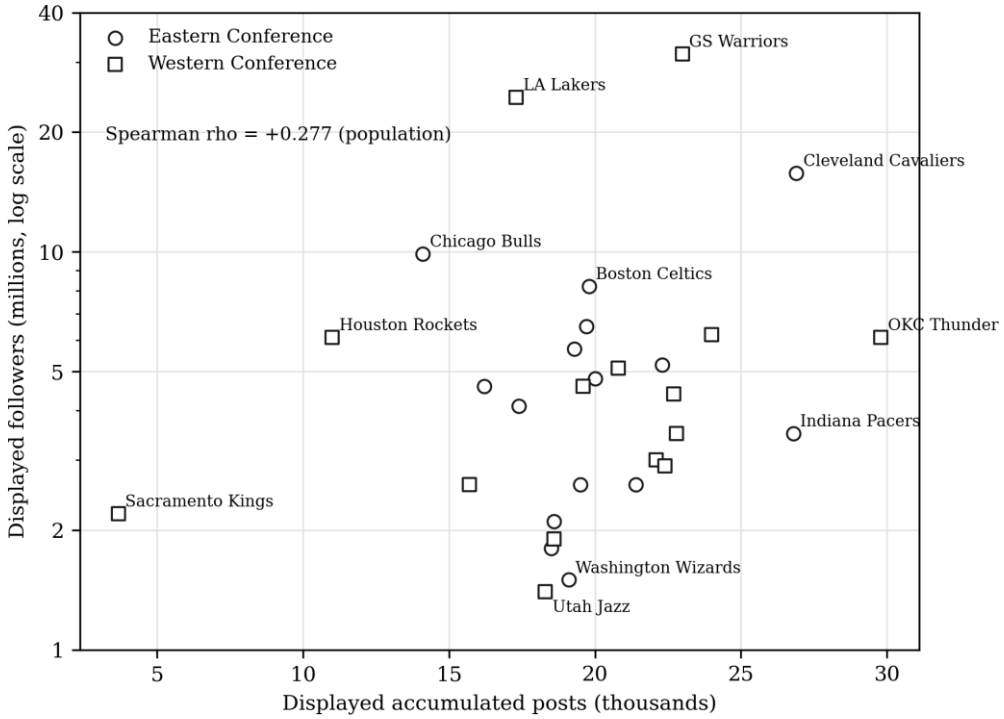


Figure 4. Relationship between displayed accumulated posts and displayed followers for the 30 NBA team accounts (followers on a logarithmic axis; Eastern Conference circles, Western Conference squares; selected accounts labeled; counters abbreviated by Instagram at varying precision; Spearman rho is a descriptive population coefficient)

5.5. Rank discordance and contrasting configurations

Figure 5 plots the difference between each team's post rank and follower rank. Positive values identify accounts whose audience rank is higher than their content rank, and negative values identify the reverse. The largest positive discordances belong to the Chicago Bulls (24 places), Los Angeles Lakers (23), and Houston Rockets (21), each of which holds a top-nine audience with a bottom-six post stock. The largest negative discordances belong to the Indiana Pacers (-15), Portland Trail Blazers (-13), Phoenix Suns (-12), and Charlotte Hornets (-11), each with a top-eleven post stock and an audience ranked eighteenth or lower. Fourteen accounts fell within five places on the two rankings, including the LA Clippers and Philadelphia 76ers accounts, which occupied identical positions on both.

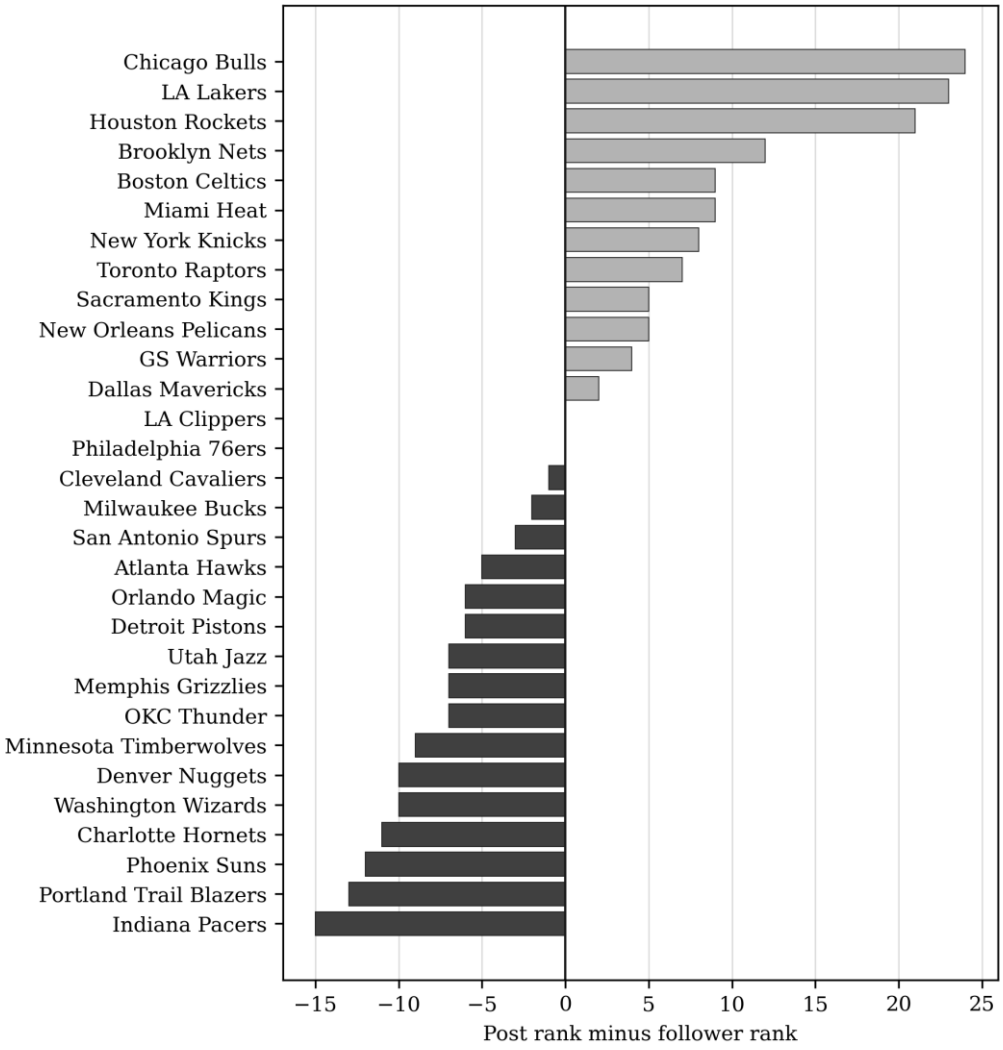


Figure 5. Rank difference between content accumulation and audience scale for each NBA team account (post rank minus follower rank; negative values indicate a higher position on posts than on followers; ties share the lower rank)

Table 6 assembles five contrasting configurations from the joint tertile positions. The first combines a high audience with a high content stock and a mid or low following count, exemplified by the Warriors, Cavaliers, and Thunder accounts. The second combines a high audience with a low content stock: the Lakers account, which also follows the fewest accounts in the league, and the Bulls and Rockets accounts, which follow comparatively many. The third combines a high content stock with a low or middle audience, as in the Pacers, Suns, Nuggets, and Trail Blazers accounts. The fourth combines a low audience with a high following count, as in the Hornets, Grizzlies, Magic, and Pistons accounts. The fifth is the Sacramento Kings account, which combines the smallest content stock in the league by a wide margin with a middle-range audience and following count. The following count cuts across all of these groupings. The ten accounts in the highest following tertile were spread five, two, and three across the low, middle, and high follower tertiles. The ten accounts following the fewest others included the two largest audiences in the league alongside the Wizards and Hawks accounts in the lowest follower tertile.

Table 6. Contrasting visibility configurations identified from joint tertile positions on posts, followers, and following (ranks out of 30; ties share the lower rank)

Configuration	Teams (post rank / follower rank / following rank)	Reading within the framework
High audience with high content stock	Golden State Warriors (5 / 1 / 16); Cleveland Cavaliers (2 / 3 / 21); San Antonio Spurs (4 / 7 / 6); Oklahoma City Thunder (1 / 8 / 14)	Audience scale and content accumulation aligned; following counts range from restricted to extensive
High audience with low content stock	Los Angeles Lakers (25 / 2 / 30); Chicago Bulls (28 / 4 / 10); Houston Rockets (29 / 8 / 3)	Largest rank discordances in the population; audience scale detached from retained content; following counts range from the smallest to the third largest
High content stock with middle or low audience	Indiana Pacers (3 / 18 / 9); Phoenix Suns (6 / 18 / 23); Denver Nuggets (10 / 20 / 28); Portland Trail Blazers (8 / 21 / 5); Minnesota Timberwolves (7 / 16 / 27)	Retained content does not translate into audience rank; no common following count
Low audience with extensive following	Charlotte Hornets (11 / 22 / 1); Memphis Grizzlies (20 / 27 / 2); Orlando Magic (20 / 26 / 7); Detroit Pistons (22 / 28 / 8)	Accounts following the most others cluster in the lowest follower tertile, but large following counts are also found among large audiences (Rockets, Spurs)
Minimal content stock	Sacramento Kings (30 / 25 / 15)	Smallest post stock, less than a fifth of the population median; the cross-sectional counter does not reveal whether this resulted from archiving, deletion, account history, posting practices, or another cause; audience and following in the middle range

For completeness, an audience-to-content-stock ratio was computed as displayed followers divided by displayed posts. It ranged from 77 followers per accumulated post (Utah Jazz) to 1,416 (Los Angeles Lakers), with a median of 234. The ratio is reported only to make the discordance visible in a single number. It is not a measure of efficiency, productivity, engagement, or content effectiveness, because it relates a stock built over fourteen years to a count of subscribers observed at one moment, and both components are abbreviated displays of varying precision.

6. Discussion

6.1. Content accumulation and audience scale

The first research question asked how the three counters are distributed, and the answer is that they are distributed very differently within the same population. Post stocks occupy a narrow band, which is unsurprising for accounts opened within the same two-year period, although the data do not show whether they have since been managed continuously or on similar routines. Follower counts occupy no such band. On that contrast alone, retained post volume is not what separates the largest audiences from the rest. The second question asked about association, and a rank correlation of 0.277 between posts and followers means that accounts with larger content stocks lean only slightly toward larger audiences. Discordance shows why the association is so weak: some of the league's largest audiences belong to accounts with some of its smallest content stocks, while some of the largest content stocks sit with audiences in the middle of the ranking.

This is not a finding that posting is unproductive, or that a team with a large post stock and a modest audience is underperforming. A post counter is a net stock: an account that has archived or deleted content shows a smaller number however active it has been, and for the Sacramento Kings account, the smallest stock in the league, a cross-sectional counter gives no way of telling whether archiving, deletion, account history, posting practice, or something else produced that position. What the result does show is that content accumulation and audience scale are analytically distinct, and the framework keeps them apart by separating the processes that produce the two counters. Inferring one counter from the other is unwarranted on this evidence, and the direction of any causal relation between activity and audience is left open by a single snapshot.

6.2. Concentrated displayed audience scale

Audience scale, the subject of the third research question, is concentrated in a way that retained post stock is not: two accounts hold about three in ten of all displayed NBA team followers, five hold about half, and the follower Gini coefficient of 0.445 stands against a post-stock Gini of 0.125 in the same 30 accounts. Cumulative-advantage accounts, in which a favorable relative position becomes a resource for further gains [22, 23], and descriptions of digital attention as structurally concentrated [25, 26], both fit this shape. A reader could go further and attribute it to sporting success, since the two dominant accounts belong to franchises with long championship histories and globally recognized players, but a cross-sectional design gives no purchase on that explanation. Concentration was observed at one moment; growth, path dependence, and the contribution of on-court results were not measured, and cumulative advantage is offered as an interpretation of the shape of the distribution, not as a tested mechanism.

Where the contrast occurs matters as much as its size. Retained posts and displayed followers diverge sharply among organizations that share one league and one platform, and that is the strongest support in the data for treating the counters as empirically and conceptually distinct, although it explains nothing about why any particular franchise sits where it does. The distance between the two Gini coefficients is the plainest expression of the article's central claim, that counters presented within one display architecture are not commensurable in what they record.

6.3. Connective selectivity

Accounts followed showed weak negative rank associations with follower scale and with accumulated posts, and the extremes make the pattern concrete. The Lakers follow fewer accounts than any other team and have the second-largest displayed audience, while the next most restricted accounts, the Heat, Nuggets, Timberwolves, and Mavericks, are scattered through the middle of the audience distribution. At the other end, the Hornets follow the most accounts and sit in the lowest follower tertile, where the Grizzlies, Magic, and Pistons, which also follow comparatively many, sit as well. So the cross-sectional results show no systematic rank alignment between outgoing connectivity and the other two counters, and they leave the teams' following decisions unexplained. Nothing here shows that following few accounts confers prestige or that following many produces engagement; what the evidence supports is the narrower claim that outgoing connectivity, read as connective selectivity, is a distinct dimension of platformed visibility on which comparable organizations occupy markedly different positions. Because the following count records neither reciprocity nor the identity of the followed accounts, nothing about network centrality can be inferred from it, a limitation that applies to any profile-level use of connectivity counts [27].

6.4. Theoretical contribution

A platform's standardized counters are produced by different practices, and the NBA evidence shows that they need not align; that is what the result adds to the literature on organizational visibility. Affordance and behavioral-visibility research describes the general condition under which organizational conduct becomes observable to third parties [10, 11]. Commensuration theory explains how three unlike quantities come to receive one judgment: retained post stock, displayed audience scale, and outgoing connectivity occupy one row of the header, and that placement encourages readers to fold them together even though notation and precision vary with magnitude [17, 18]. Across the NBA accounts the three rankings and distributions do not behave as one measure. Post stock is nearly uniform, audience scale is highly concentrated, and the following count lines up with neither. Cumulative-advantage and attention-economy accounts give the concentration an interpretive context without being tested [22, 23, 25]. Platform infrastructure, standardized counters, behavioral visibility, commensuration, distinct configurations, and unequal displayed audience scale thus sit in one

explanatory chain, with the three dimensions kept apart and no longitudinal mechanism imported that the data could not test.

The full-population design strengthens this claim in one specific way. Heterogeneous configurations observed across different sports, leagues, or platforms could always be attributed to those differences. Observed within one league on one platform, they cannot be attributed to sport, league membership, or platform architecture, although franchise-level differences remain uncontrolled. The persistence of contrasting configurations among 30 organizations that share a competitive calendar and a metric architecture is evidence that the dimensions are analytically separable, whatever the reasons for any franchise's position.

6.5. Implications for sport marketing and organizational practice

For practitioners, the central implication is that no single Instagram counter should stand in for the others. A benchmarking exercise that ranks teams by followers tells a different story from one that ranks them by content stock, and neither says anything about the number of accounts followed, so organizations comparing themselves with peers should compare the same counter and state which one they mean. Audience scale deserves particular care: concentration is severe and the largest audiences do not belong to the largest content stocks, so an organization with a mid-sized audience is not necessarily doing less than a larger rival, and an organization with a large content stock has no reason to expect its audience rank to follow. The following count, finally, varies so widely within the league that organizations plainly take very different positions on outgoing association, and its weak association with audience scale gives no descriptive basis for expecting audience rank to follow from the number of accounts followed. Whether any of these patterns holds over time, or reflects what audiences actually see and do, is a question that longitudinal and post-level data would have to answer.

7. Limitations and future research

The study is a cross-sectional snapshot. Public counters change continuously, so the values reported here describe a window of three consecutive days after the 2025-2026 season, not a stable property of the accounts, and the team-specific capture date within that window was not recorded. Instagram displayed the follower and post counts of larger accounts in abbreviated K and M notation at varying precision, generally one to three significant digits, so all aggregates, ratios, and coefficients are approximate. Followers do not measure reach, impressions, engagement, loyalty, or authenticity, and no attempt was made to distinguish active from inactive or authentic from inauthentic followers. Cumulative posts do not reveal posting frequency during the season, and archived or deleted posts affect the displayed stock in ways the data cannot detect, so the reason for any individual post stock, including the smallest in the population, remains unobserved. Following counts do not establish reciprocal connections, the composition of the followed set, or network centrality.

No player-account data were analyzed and no post-level likes, comments, views, or impressions were collected. The design identifies no causal relationship in either direction between retained content, displayed audience, and connectivity, and cumulative advantage serves only as an interpretive lens. The results describe NBA team accounts on Instagram and nothing wider; other leagues, sports, and platforms have their own institutional conditions, affordances, and metric architectures, and carrying the findings over to them would require checking. Public counters also disclose nothing about algorithmic distribution, which determines what followers actually see.

Several extensions follow from these limits. Capturing the same counters at intervals across a season and its off-season would relate follower change to posting activity and to the competitive calendar. Post-level data on content type and interaction would separate what was posted from how audiences responded. Comparative work across leagues and platforms would show whether the three

dimensions remain separable under other institutional conditions. Interviews with team communication staff would establish how following policies are set and what organizations believe the counters signal, tying the observed configurations to the practices that produce them.

8. Conclusion

Taking all 30 official NBA team Instagram accounts together, as a complete population, made it possible to ask whether the three counters on every profile describe one dimension of organizational visibility or several. In the verified postseason snapshot, the three counters represent separate dimensions of organizational visibility. Post stocks were tightly clustered; follower counts were concentrated, with two accounts holding about 30 percent of the combined total and five about 49 percent; and following counts ran from 88 to 1,915 with only weak negative rank associations to the other two counters. The rank correlation between posts and followers was weak, and the discordances between the two rankings produced accounts with large audiences and small content stocks as well as accounts with large content stocks and middling audiences, all within one league where sport, competitive calendar, platform, and metric architecture are constant and only franchise-level differences remain uncontrolled. What the comparison does not explain is why any particular franchise sits where it does; growth, engagement, and the practices behind the numbers are beyond a single snapshot. The shared header nonetheless invites a reader to take a large post count, a large follower count, and a small following count as three signs of one success, and the weak association between posts and followers, together with the independence of the following count from both, is the result that contradicts that reading. Post stock, audience scale, and outgoing connectivity arise from different processes, and the framework keeps them apart without claiming more than rounded counters captured at one moment can bear. Comparisons between accounts should therefore set follower counts against follower counts, post stocks against post stocks, and following counts against following counts, taken at the same capture window, and should treat none of them as a summary of digital success.

9. Declaration of Generative Artificial Intelligence-Assisted Work

During preparation of this manuscript, the author used generative artificial intelligence tools for language refinement and assistance with organizing the written presentation. The research questions, study design, manual data collection, data verification, analysis, interpretation, references, and final scholarly judgments remained the author's responsibility. The author reviewed and revised the complete manuscript and accepts full responsibility for its accuracy and integrity. This disclosure accords with the Committee on Publication Ethics (COPE) position that artificial-intelligence tools cannot assume authorship and that human authors remain responsible for the work submitted under their names [33].

References

[1] C. Anagnostopoulos, P. Parganas, S. Chadwick, and A. Fenton. "Branding in pictures: Using Instagram as a brand management tool in professional team sport organisations." *European Sport Management Quarterly*, vol. 18, no. 4, pp. 413-438, 2018. https://doi.org/10.1080/16184742.2017.1410202

[2] K. Filo, D. Lock, and A. Karg. "Sport and social media research: A review." *Sport Management Review*, vol. 18, no. 2, pp. 166-181, Apr. 2015. https://doi.org/10.1016/j.smr.2014.11.001

[3] N.K. Baym. "Data not seen: The uses and shortcomings of social media metrics." *First Monday*, vol. 18, no. 10, Oct. 2013. https://doi.org/10.5210/fm.v18i10.4873

[4] M. Cha, H. Haddadi, F. Benevenuto, and K.P. Gummadi. "Measuring user influence in Twitter: The million follower fallacy," in *Proc. 4th Int. AAAI Conf. Weblogs and Social Media (ICWSM)*, 2010, pp. 10-17. https://doi.org/10.1609/icwsm.v4i1.14033

[5] P. Parganas, C. Anagnostopoulos, and S. Chadwick. "'You'll never tweet alone': Managing sports brands through social media." *Journal of Brand Management*, vol. 22, no. 7, pp. 551-568, Sep. 2015. https://doi.org/10.1057/bm.2015.32
[6] D. Maderer, P. Parganas, and C. Anagnostopoulos. "Brand-image communication through social media: The case of European professional football clubs." *International Journal of Sport Communication*, vol. 11, no. 3, pp. 319-338, Sep. 2018. https://doi.org/10.1123/ijsc.2018-0086
[7] Y. Su, B.J. Baker, J.P. Doyle, and T. Kunkel. "The rise of an athlete brand: Factors influencing the social media following of athletes." *Sport Marketing Quarterly*, vol. 29, no. 1, pp. 33-46, Mar. 2020. https://doi.org/10.32731/smq.291.302020.03
[8] M.L. Naraine and M.M. Parent. "Illuminating centralized users in the social media ego network of two national sport organizations." *Journal of Sport Management*, vol. 30, no. 6, pp. 689-701, Nov. 2016. https://doi.org/10.1123/jsm.2016-0067
[9] M.L. Naraine. "Follower segments within and across the social media networks of major professional sport organizations." *Sport Marketing Quarterly*, vol. 28, no. 4, pp. 222-233, Dec. 2019. https://doi.org/10.32731/smq.284.122019.04
[10] J.W. Treem and P.M. Leonardi. "Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association." *Annals of the International Communication Association*, vol. 36, no. 1, pp. 143-189, 2013. https://doi.org/10.1080/23808985.2013.11679130
[11] P.M. Leonardi and J.W. Treem. "Behavioral visibility: A new paradigm for organization studies in the age of digitization, digitalization, and datafication." *Organization Studies*, vol. 41, no. 12, pp. 1601-1625, Dec. 2020. https://doi.org/10.1177/0170840620970728
[12] M. Flyverbom, P. Leonardi, C. Stohl, and M. Stohl. "The management of visibilities in the digital age: Introduction." *International Journal of Communication*, vol. 10, pp. 98-109, 2016. Available: https://ijoc.org/index.php/ijoc/article/view/4841
[13] T. Gillespie. "The politics of 'platforms'." *New Media & Society*, vol. 12, no. 3, pp. 347-364, May 2010. https://doi.org/10.1177/1461444809342738
[14] J. van Dijck and T. Poell. "Understanding social media logic." *Media and Communication*, vol. 1, no. 1, pp. 2-14, Aug. 2013. https://doi.org/10.17645/mac.v1i1.70
[15] T. Bucher. "Want to be on the top? Algorithmic power and the threat of invisibility on Facebook." *New Media & Society*, vol. 14, no. 7, pp. 1164-1180, Nov. 2012. https://doi.org/10.1177/1461444812440159
[16] K. Cotter. "Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram." *New Media & Society*, vol. 21, no. 4, pp. 895-913, Apr. 2019. https://doi.org/10.1177/1461444818815684
[17] W.N. Espeland and M.L. Stevens. "A sociology of quantification." *European Journal of Sociology*, vol. 49, no. 3, pp. 401-436, Dec. 2008. https://doi.org/10.1017/S0003975609000150
[18] W.N. Espeland and M.L. Stevens. "Commensuration as a social process." *Annual Review of Sociology*, vol. 24, pp. 313-343, Aug. 1998. https://doi.org/10.1146/annurev.soc.24.1.313
[19] C. Gerlitz and A. Helmond. "The like economy: Social buttons and the data-intensive web." *New Media & Society*, vol. 15, no. 8, pp. 1348-1365, Dec. 2013. https://doi.org/10.1177/1461444812472322
[20] A.E. Marwick. "Instafame: Luxury selfies in the attention economy." *Public Culture*, vol. 27, no. 1, pp. 137-160, Jan. 2015. https://doi.org/10.1215/08992363-2798379
[21] D. Opelík, J. Voráček, J. Šíma, and A. Michlová. "Exploring Instagram communication: Usage of Instagram as a marketing tool in professional basketball clubs." *Studia Sportiva*, vol. 18, no. 2, Dec. 2024. https://doi.org/10.5817/StS2024-2-15
[22] R.K. Merton. "The Matthew effect in science." *Science*, vol. 159, no. 3810, pp. 56-63, Jan. 1968. https://doi.org/10.1126/science.159.3810.56
[23] T.A. DiPrete and G.M. Eirich. "Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments." *Annual Review of Sociology*, vol. 32, pp. 271-297, Aug. 2006. https://doi.org/10.1146/annurev.soc.32.061604.123127
[24] M.J. Salganik, P.S. Dodds, and D.J. Watts. "Experimental study of inequality and unpredictability in an artificial cultural market." *Science*, vol. 311, no. 5762, pp. 854-856, Feb. 2006. https://doi.org/10.1126/science.1121066
[25] M. Hindman. *The Internet Trap: How the Digital Economy Builds Monopolies and Undermines Democracy*. Princeton, NJ: Princeton University Press, 2018.
[26] J.G. Webster. *The Marketplace of Attention: How Audiences Take Shape in a Digital Age*. Cambridge, MA: MIT Press, 2014.
[27] J. Howison, A. Wiggins, and K. Crowston. "Validity issues in the use of social network analysis with digital trace data." *Journal of the Association for Information Systems*, vol. 12, no. 12, pp. 767-797, Dec. 2011. https://doi.org/10.17705/1jais.00282

[28] T. Venturini, L. Bounegru, J. Gray, and R. Rogers. "A reality check(list) for digital methods." *New Media & Society*, vol. 20, no. 11, pp. 4195-4217, Nov. 2018. https://doi.org/10.1177/1461444818769236
[29] D. Freelon. "Computational research in the post-API age." *Political Communication*, vol. 35, no. 4, pp. 665-668, 2018. https://doi.org/10.1080/10584609.2018.1477506
[30] A. Bruns. "After the 'APIcalypse': Social media platforms and their fight against critical scholarly research." *Information, Communication & Society*, vol. 22, no. 11, pp. 1544-1566, 2019. https://doi.org/10.1080/1369118X.2019.1637447
[31] R. Dorfman. "A formula for the Gini coefficient." *The Review of Economics and Statistics*, vol. 61, no. 1, pp. 146-149, Feb. 1979. https://doi.org/10.2307/1924845
[32] M.O. Lorenz. "Methods of measuring the concentration of wealth." *Publications of the American Statistical Association*, vol. 9, no. 70, pp. 209-219, Jun. 1905. https://doi.org/10.2307/2276207
[33] COPE Council. "COPE position - Authorship and AI - English." Committee on Publication Ethics, 2024. https://doi.org/10.24318/cCVRZBmssvg