



Sourcing Reach, Interview Bottlenecks and Offer Dropout: A Recruitment Funnel Analysis at an AI Services Company in India

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Abstract: Small technology firms hire through the same job platforms as large ones, but they have no analytics team to show where their process loses candidates. This study follows the hiring funnel at an Indian AI services company across two closed requisitions: an AI Native Engineer/Software Development Engineer role with two openings and a Product Manager role with one. The author handled sourcing, screening, interview coordination and offer follow-up as an intern and kept a candidate-level tracker throughout. The tracker was checked against Keka ATS records, Naukri.com NVite emails and the Indeed employer dashboard.

The firm received 4,178 applications from LinkedIn, Indeed, Naukri.com and its own Keka ATS page. Naukri.com supplied 65.4% of them and had the lowest shortlisting rate (2.78%). LinkedIn supplied 2.5% and had the highest (15.24%). Of 150 shortlisted candidates, the count fell from 65 to 19 at the founder-led leadership round, a drop of 70.8%. Nine candidates received offers and three joined. Average time to hire was 18.5 days, inside the 30 to 45 day benchmark used here. Speed was not the problem at this firm. Candidates were lost at the top of the funnel, in one interview round, and between offer and joining. The paper ends with six changes the firm can make, most of them without new spending.

Keywords: recruitment funnel, e-recruitment, time to hire, offer dropout, applicant tracking system, technology startup

I. INTRODUCTION

The company in this study is a young Indian firm that builds AI agent solutions and software products. Its headcount more than doubled in about eight months, so it has to keep hiring, and it does so through four digital channels: LinkedIn, Indeed, Naukri.com and the company's own page on Keka, its applicant tracking

system (ATS). Both co-founders sit on the leadership interview round, so every candidate who gets that far meets them.

Three questions guide this study. Which channel brings in candidates worth interviewing? At what stage do candidates leave? And is a fast process also an effective one? The author answered them from the inside. As a recruitment intern working under the HR Head, the author ran sourcing, screening, interview coordination and offer follow-up for two requisitions, and recorded every application and every stage outcome as it happened. That gives a complete, stage-by-stage record of two closed hiring cycles, which outside researchers rarely get from a company of this size.

Earlier work on online recruitment mostly asks why firms adopt it and how well it works across many employers (Galanaki, 2002; Parry & Tyson, 2008). This paper adds a single-firm case with candidate-level funnel data from a small Indian technology company: 4,178 applications, 150 shortlisted candidates, nine offers and three joiners. It also ends with changes the firm can make without much new spending.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

A. Literature Review

Galanaki (2002) asked UK IT companies why they recruit online. The study tested how perceived attributes of the practice, among them cost, cycle time, response rate, response quality and the ability to reach passive job seekers, affected the decision to use it. Parry and Tyson (2008) later combined a large longitudinal survey with twenty interviews of users and providers. They found online recruitment widely used by UK organisations but with mixed success, which is why it had not taken over the market as early predictions suggested. Parry and Wilson (2009) looked at the adoption decision itself, interviewing and surveying HR managers and relating their answers to diffusion of innovation theory and the



theory of planned behaviour. By the time of these studies the adoption question was mostly settled. Whether a particular channel works for a particular employer was not.

Applicant pools differ a lot, even for similar jobs. Connerley, Carlson and Mecham (2003) analysed 391 applicant pools across 18 job families and found that pool quality varied substantially within and across families. Reputation is one possible reason. Turban and Cable (2003) ran two studies using actual applicant data from business school career offices, not stated intentions, and found that firm reputation affected both the number and the quality of people who applied. Ambler and Barrow (1996) had earlier described the employer brand as the functional, economic and psychological benefits of employment that people associate with an employer, which suggests a firm may look different to the audiences of different platforms.

Less is known about what happens after an offer. Lyons, Moorman and Michel (2024) studied applicant ghosting, where a candidate stops all contact, from the applicant's side and tied it to personality traits and to how applicants were treated during hiring. Speer et al. (2026) examined new hires who accept an offer and then disappear before day one. In a multi-year archival dataset ($N = 157,154$) from a large telecommunications company, 4.1% of accepted offers ended this way. Risk was higher with longer gaps between offer and start date, for non-referral hires, where communication before joining was weaker, and where candidates held external offers.

B. Theoretical Background

Flippo (1984) described recruitment as two jobs: finding prospective employees and encouraging them to apply. The first is sourcing and the second is attraction, and this study looks at both. The analysis rests on a recruitment funnel, a sequence borrowed from the AIDA model in marketing (awareness, interest, desire, action). Candidates enter at the top as applicants, and the count shrinks at every stage. A stage's conversion rate is the share of candidates who get through it from the stage before. The model is useful because it asks where candidates are lost as well as how many.

The interview design follows a competency approach (Boyatzis, 1982), in which each assessment looks for specific skills and behaviours linked to job success. At the company the four rounds test different things. The

HR round covers communication, attitude and understanding of the role. The technical round covers domain knowledge and problem solving. The founders' round looks at strategic thinking and ownership. The final panel, held in person at the company's office, brings together several evaluators.

III. MATERIALS AND METHODS

A. Research Objectives

The study has three objectives. The first is to map the 13-stage hiring workflow at the company, from requirement intake to joining, and to find where candidates drop out. The second is to measure hiring efficiency through shortlisting rate, stage-wise conversion and time to hire. The third is to compare LinkedIn, Indeed, Naukri.com and Keka ATS on application volume and shortlisting yield.

B. Research Design and Data Collection

This is a single-organisation, descriptive case study carried out from inside the process. The author worked at the company for a time being and handled two requisitions: REQ-01, an AI Native Engineer/Software Development Engineer role with two openings, and REQ-02, a Product Manager role with one opening. Other roles stayed open in Keka ATS during the period but were not closed, and they are left out.

Both requisitions followed the same 13 stages. The HR Head briefed the author on each role, and the author drafted the job description and posted it on LinkedIn, Indeed, Naukri.com and Keka. On LinkedIn the author also searched actively with Boolean strings and InMail. Resumes were screened against the job description, shortlisted candidates got a phone screen, and an assessment test followed. Four interview rounds came next: HR, technical, COO and CEO, and an in-person panel. Document and background verification came before the offer, so credentials were confirmed before the company committed to pay. After the offer, the process moved to appointment letters and onboarding in Keka HRIS. Candidate updates ran alongside stages three to seven.

The main data source was an applicant tracker the author kept throughout. For each candidate it recorded the source platform, the shortlisting decision, the phone-screen result, the outcome of each interview round, document and background verification status, offer details, the joining outcome, and the dates of job posting



and offer acceptance. Dropout reasons were noted where candidates gave them. The author checked the tracker against three independent records: Keka ATS screenshots, Naukri.com NVite email records and the Indeed employer dashboard. Every application received for the two requisitions is in the data, so there is no sample.

C. Analytical Framework

Four measures are used. Shortlisting rate is shortlisted candidates divided by applications received. Stage conversion is the number of candidates at a stage divided by the number at the stage before. Time to hire is the number of days from job posting to offer acceptance. Offer acceptance rate is joiners divided by offers released. A range of 30 to 45 days, taken as typical for IT roles, is the benchmark for time to hire. All figures are descriptive. Two requisitions give too few closed hires for significance tests, so the paper makes no claims of statistical significance.

IV. DATA ANALYSIS AND DISCUSSION

A. Volume and Quality by Platform

Table I shows where the 4,178 applications came from and how many turned into shortlisted candidates.

TABLE I
APPLICATIONS AND SHORTLISTING BY PLATFORM (BOTH REQUISITIONS)

Platform	Applications	Share	Shortlisted	Rate
LinkedIn	105	2.5%	16	15.24%
Indeed	427	10.2%	20	4.68%
Naukri.com	2,734	65.4%	76	2.78%
Keka ATS	912	21.8%	38	4.17%
Total	4,178	100%	150	3.59%

Volume and quality pulled in opposite directions. Naukri.com sent 2,734 applications, 65.4% of the total, but only 76 of them (2.78%) were shortlisted. About 97 of every 100 Naukri.com applicants did not meet the screening criteria. LinkedIn sent just 105 applications and 16 were shortlisted (15.24%). Indeed (4.68%) and

the Keka ATS page (4.17%) sat in between. Naukri.com still supplied half of all shortlisted candidates (76 of 150) because of its size, as Fig. 1 shows, so its low yield cost screening time but the channel still filled half the shortlist.

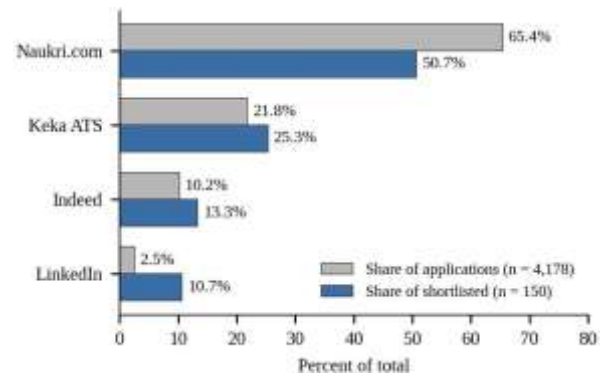


Fig. 1. Share of applications and share of shortlisted candidates, by platform.

Table II splits the rates by role.

TABLE II
SHORTLISTING RATE BY PLATFORM AND ROLE

Platform	AI Native Engineer/SDE	Product Manager
LinkedIn	8 of 85 (9.4%)	8 of 20 (40.0%)
Indeed	15 of 269 (5.6%)	5 of 158 (3.2%)
Naukri.com	68 of 1,456 (4.7%)	8 of 1,278 (0.6%)
Keka ATS	30 of 644 (4.7%)	8 of 268 (3.0%)
Total	121 of 2,454 (4.9%)	29 of 1,724 (1.7%)

The gap between LinkedIn and Naukri.com is wider for the Product Manager role. LinkedIn shortlisted 8 of 20 applicants (40.0%). Naukri.com shortlisted 8 of 1,278 (0.6%). The LinkedIn figure rests on only 20 applications, so it is a signal and not a stable rate. Indeed shortlisted 5 of 158 (3.2%) for the same role, close to the Keka ATS page (3.0%) and below its own 5.6% for the engineer role. The Product Manager opening closed in about seven days.

LinkedIn was the one channel the author worked actively. Boolean search and InMail went to candidates for the AI and ML roles, while Indeed, Naukri.com and Keka waited for people to apply. The spread across four platforms at one employer is a small-scale version of the mixed success Parry and Tyson (2008) reported across



UK organisations. Employer branding is a second possible reason. The company posts project wins and staff recognition on its LinkedIn company page, and Ambler and Barrow (1996) and Turban and Cable (2003) would expect that to change who applies. The data here cannot separate active sourcing, platform audience and brand effects, and no test was run to do so.

B. The Recruitment Funnel

Table III follows candidates from application to joining, and Fig. 2 shows the same counts.

TABLE III.
TAGE-WISE MOVEMENT OF CANDIDATES, BOTH
REQUISITIONS

Stage	Candidates	From previous stage
Applications received	4,178	NA
Shortlisted	150	3.6%
Phone screening	150	100%
HR round	131	87.3%
Technical round	65	49.6%
Leadership round (COO and CEO)	19	29.2%
Final panel	9	47.4%
Document and background checks	9	100%
Offers released	9	100%
Joined	3	33.3%

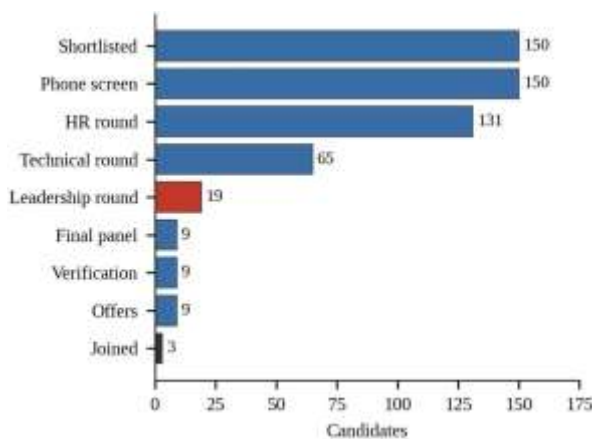


Fig. 2. Candidates remaining at each stage after shortlisting. The leadership round is shown in red.

Of 4,178 applications, 150 (3.59%) were shortlisted, and all 150 had a phone screen. The HR round passed

131 of them (87.3%). The technical round was a harder filter: 65 of 131 moved on (49.6%). The leadership round was harder still. The count fell from 65 to 19, a drop of 70.8% and the steepest after the first screen. The final panel took 9 of those 19 (47.4%). All 9 passed document and background checks and received offers.

The leadership round needs both co-founders and the candidate in the same slot, and finding one sometimes took three to five days after a candidate cleared the technical round. In the engineer cycle, several strong candidates waited for that slot. At least two told the author they held competing offers, and one accepted another job before the round could be scheduled. The tracker cannot say how many of the 46 candidates lost at this stage failed on merit and how many left while waiting. Both are plausible. A competency-based round (Boyatzis, 1982) that screens for ownership and strategic thinking should filter hard, but the scheduling delay is a cost the firm can remove without lowering the bar.

The first screen removed 96.4% of applications, which is mostly a workload problem for the recruiter. The author used a quick-scan checklist covering college, stream, CGPA and relevant experience to cope, and the load still peaked when three or four requisitions ran at once.

C. Time to Hire and Offer Outcomes

Table IV gives time to hire and offer outcomes for each requisition.

TABLE IV.
IME TO HIRE AND OFFER OUTCOMES

Requisition	Time to hire	Offers	Joined	Did not join
REQ-01 (Engineer/SDE)	about 30 days	5	2	3
REQ-02 (Product Manager)	about 7 days	4	1	3
Total / mean	18.5 days	9	3	6

Both openings closed inside or below the 30 to 45 day benchmark. REQ-01 took about 30 days, from an April 2026 posting to a May 2026 acceptance. REQ-02 took about seven. The mean of 18.5 days comes from



only two requisitions, so it describes this period and should not be read as a firm-wide benchmark.

The weak point is after the offer. Nine offers went out and three candidates joined (33.3%). Three of five engineer offers and three of four Product Manager offers did not convert. Three patterns showed up. Some candidates took a higher-paying offer from another company while waiting between rounds. Some wanted more pay than the package allowed and chose not to negotiate. One accepted the offer, did not appear on the joining date and did not reply. A dropout often meant restarting part of the pipeline and pushing back the closing date.

These patterns match factors Speer et al. (2026) link to new hires who vanish before day one: external offers and weak contact before joining. The two rates cannot be compared directly. Their 4.1% counts accepted offers that ended in no-shows at one large employer, while the 66.7% here counts every offer that did not end in a joining, including open declines. Referrals at the company were occasional and informal, and Speer et al. found non-referral hires more likely to disappear.

D. Screening Volume for the Fresher Role

One screening spell shows the volume pressure on the fresher engineer opening. On 28 and 29 May 2026 the author screened 33 candidates for that role. About 18 came from IITs and IIITs, about 8 from NITs and about 7 from other colleges such as VIT. About 20 had internship experience, usually three to twelve months. Stipend expectations ran from 15K to 50K a month, and several candidates expected more than the budgeted range. Two had one-year gaps and were screened out. After a few cycles the author began raising pay expectations during the phone screen instead of after the technical round, which saved pipeline time.

V. FINDINGS, CONCLUSIONS AND SUGGESTIONS

A. Findings

Reach and yield differ by platform. Naukri.com gave 65.4% of applications and the lowest shortlisting rate (2.78%). LinkedIn gave 2.5% and the highest (15.24%), and 40.0% for the Product Manager role.

Candidates were lost at three points: the first screen (96.4% of applications), the leadership round (65 to 19, a 70.8% drop), and the offer stage (6 of 9 offers did not end in a joining).

Speed was not an issue. Time to hire averaged 18.5 days against a benchmark of 30 to 45.

Verifying documents and backgrounds before the offer cost no candidates at that step, and no post-joining dropout was linked to credential problems.

B. Conclusions

Hiring at the company is fast but leaky. Time to hire is not where the firm needs to improve. Three loss points matter more: the volume of unsuitable applications from the largest channel, the wait for the leadership round, and the gap between offer and joining. Out of 4,178 applicants, three joined.

On channels, the evidence favours working LinkedIn actively for specialist roles and treating Naukri.com as a volume source that needs fast screening. Whether the gap comes from the platform, the effort or the employer brand is not settled by this data.

C. Suggestions

Six changes follow from the data. Most need no new spending.

Pre-book the leadership round. Block recurring weekly slots in both founders' calendars and offer the next slot to a candidate on the day the technical round is cleared.

Work LinkedIn weekly for specialist roles. Set aside a fixed block for Boolean search and InMail while a technical or product role is open. Check whether a LinkedIn Recruiter Lite subscription is worth paying for at a 15.24% shortlisting yield.

Raise pay early and keep in touch. Share the pay band at the phone screen. Message candidates within 48 hours of the final panel with next steps and dates. Log the reason every time a candidate drops out.

Start a referral programme. Referrals were informal during the study. A written programme with a reward adds a fifth channel and, going by Speer et al. (2026), a lower risk of no-shows.

Use Keka ATS alerts. Set alerts for candidates who sit at one stage beyond a fixed number of days, so stalled candidates are found while they can still be saved.

Use a one-page intake form. Before a role is posted, record skills, pay range, interview panel and target closing date with the HR Head and the hiring manager,



so mismatches in requirements or pay show up before sourcing starts.

D. Limitations

Two requisitions at one company over about seven months can describe a process but cannot support firm-wide benchmarks or significance tests, and the results may not hold for larger firms or other cities. The author was both recruiter and researcher, so screening choices, job description wording and candidate messages came from the same person who reports their results. Every figure comes from dated tracker entries or system records to limit this problem, but it cannot be removed.

The author had no access to platform subscription costs or pay bands, so cost per hire by platform is not calculated. Only four channels were used, and campus hiring, agencies and walk-ins are outside the study. Document Submission Rate was planned, but the tracker did not record submission dates for every candidate, so no figure is given. Dropout reasons were recorded unevenly and are described, not counted. The counts for the final panel, document verification and background verification were set to match the nine offers on record.

E. Implications of the Study

For the company, the main implication is where to put effort. Faster processing would add little to an 18.5-day average. Calendar planning for the founders and pay conversations at the phone screen go after losses the data actually shows. For other small technology firms, the paper shows that a tracker built from ordinary tools (a spreadsheet, ATS exports and platform dashboards) is enough to find where candidates leave. For researchers, it offers a candidate-level case that can be repeated at other firms with the same four measures.

F. Future Scope of the Study

Four extensions would make the findings firmer. Cost per hire by platform needs subscription and posting costs the author could not see. Tracking joiners for six to twelve months would show whether the channel a person came through predicts retention and performance. A structured dropout log, filled in at the time of every withdrawal, would let later studies count reasons that this one only describes. Repeating the funnel analysis at other small technology firms, and testing whether pre-booked founder slots shorten the wait for the leadership round, would show how far these results travel.

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