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ABSTRACT

Misaligned incentives within organizations may explain why firms fail to adopt or fully benefit from productive technologies. We conducted a randomized controlled trial in Indian garment factories in which units received an anonymous worker-management communication technology, this technology paired with incentives for HR managers to communicate effectively with workers, or neither (control). We find that the technology alone had no impacts relative to control. But pairing the technology with HR incentives increased productivity by 5%, reduced absenteeism by 13%, and raised worker earnings by 3%. Impacts were driven by greater HR responsiveness and increased worker reporting of production-related issues.

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A randomized controlled trials registry entry is available at
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1 Introduction

Investments in new technology often fail to translate into productivity gains. Solow's observation, that the computer age was visible everywhere except in the productivity statistics, prompted a large literature seeking to reconcile rapid technological investment with disappointing measured returns (Brynjolfsson, 1993; Solow, 1987). A central resolution to this puzzle is that information technologies raise productivity only in conjunction with complementary investments in organizational structure, work practices, and human capital; firms that adopt the technology without these complements capture little of its potential value (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000). More recent work formalizes this lag as a "productivity J-curve," in which measured returns to a new technology are initially low or even negative because the complementary organizational investments that make it productive take time to build (Brynjolfsson et al., 2021).

This hypothesis, that organizational factors govern whether technology delivers returns, has been advanced largely on the basis of firm-level observational data. The observed patterns are consistent with complementarity, but organizational complements are chosen rather than varied prospectively, leaving their causal role hard to pin down. Credible causal evidence requires exogenous variation in the organizational complement itself, and studies that provide it, especially via a randomized design, remain rare. A notable exception is Atkin et al. (2017), who randomize the introduction of a profitable production technology and show that worker-side incentive misalignment slows its adoption. We provide, to our knowledge, the first experimental evidence on a distinct and central margin: the alignment of managerial incentives to respond to what a technology enables. The technology we evaluate is a communication tool that allows workers to raise grievances and suggestions to management. By design, its returns should depend on organizational response: workers' willingness to voice issues, and any resulting gains in conditions or productivity, turn on whether management is able and motivated to act on what is raised.

Understanding why managerial response is the binding input requires understanding what worker voice is meant to accomplish, and why it so often falls short. Hirschman's foundational insight was that when workers can express their suggestions, grievances, and concerns to management, they are less likely to exit and more likely to contribute to firm success (Hirschman, 1970).

A large body of work has borne out this thesis, and recent experimental studies in particular show that strengthening workers' ability to communicate with management reduces turnover and absenteeism (Adhvaryu et al., 2026, 2022), makes workplaces safer (Boudreau, 2024), and can raise productivity (Cai and Wang, 2022). When workers are dissatisfied but lack adequate channels to communicate, they express that dissatisfaction through counterproductive behavior instead, such as producing defective goods (Krueger and Mas, 2004) or deliberately selling customers the wrong items (Coviello et al., 2022).

Implicit in Hirschman's framework, however, is that voice works only if it elicits a response. Workers raise issues in the expectation that management will act; absent a credible prospect of action, the incentive to voice, and the returns to any technology that enables it, erode. Yet the determinants of organizational response have received far less attention than the determinants of voice itself. Managers, like workers, act on their own incentives and constraints, and whether they respond to what workers raise in a timely and appropriate manner is not guaranteed. This is the margin our experiment isolates.

To test whether organizational responsiveness is what makes such a technology pay off, we conducted a randomized controlled trial with Shahi Exports, India's largest garment manufacturer. In 2019, we randomly assigned 43 of Shahi's factories in southern India to one of three groups. The first received Inache, an anonymous two-way communication technology developed by Good Business Lab that allows workers to send text or voice messages to a dedicated helpline and receive responses from HR while preserving anonymity. Inache was designed for workers with limited technological literacy and does not require a smartphone. The second group received Inache together with a scheme that rewarded HR teams for resolving worker grievances promptly and appropriately, based on the timeliness of case filing, allocation, and response, the duration of resolution, and an external assessment of quality. The third group received neither and serves as the control. This design lets us separate the effect of making the communication technology available from the effect of aligning managerial incentives to act on what workers report.

We find that introducing the technology alone had no detectable effect on worker outcomes. When access to Inache was paired with HR incentives, however, the effects were substantial.

Relative to control, the combined treatment increased productivity by 5 percent, reduced absenteeism by 13 percent, and raised worker earnings by 3 percent. Turnover fell by roughly 6 percent under the combined treatment as well, though this estimate is imprecise. The contrast between the impacts of the two treatment arms is our central result: an identical technology, freely available in both, generated returns only where managerial incentives were aligned to respond to it.

The pattern of impacts on intermediate outcomes indicates that these gains operated through improved organizational response. In incentivized factories, HR teams resolved cases more quickly than in tool-only factories, with no decline in the quality of resolution, and workers grew more likely to raise issues and more confident in doing so. Factories combining the tool with incentives received nearly twice as many reports concerning production conditions as those with the tool alone. Many of these reports identified problems with direct bearing on output, such as broken equipment and high temperatures on the shop floor, suggesting that the productivity gains arose in part because an incentivized organization acted on operational problems that workers were now willing to surface.

Our findings speak to three literatures. We contribute first to the literature on technology adoption and the organizational complements that determine its returns. A long line of work, beginning with the productivity paradox, has argued that information technologies raise productivity only alongside complementary investments in organizational structure and practice (Bresnahan et al., 2002; Brynjolfsson and Hitt, 2000). Because this evidence rests largely on observational firm-level data, the causal role of these complements has been difficult to establish, and field experiments isolating it remain rare (Adhvaryu et al., 2023; Atkin et al., 2017). We provide direct experimental evidence that organizational complementarity is causal, and we locate it on a specific margin: the alignment of incentives for managers to act on what a technology enables. We thus identify managerial responsiveness as the complementary input, and managerial incentive misalignment, rather than resistance on the part of workers, as the margin that determines whether the technology pays off.

Second, we contribute to the literature on worker voice. A growing body of experimental work establishes that strengthening workers' ability to communicate with management improves a range of workplace outcomes (Adhvaryu et al., 2026, 2022; Boudreau, 2024; Cai and Wang, 2022). This work has focused on how voice changes the behavior of workers, leaving the role of organizational response comparatively unexamined. Our prior work in this setting is illustrative: we either shut down managerial responses by design (Adhvaryu et al., 2022) or found low worker utilization of a voice technology when responses were not incentivized (Adhvaryu et al., 2026). The present study shows that the returns to voice depend on whether the organization is motivated to respond, and that incentivizing response is what converts enhanced voice into measurable gains in attendance, earnings, and productivity. In this respect our results also relate to studies of workplace relationships (Adhvaryu et al., 2024; Ashraf and Bandiera, 2018; Baker et al., 2001, 2002; Bandiera et al., 2009; MacLeod and Malcomson, 1989) and of manager-worker communication and cooperation (Adhvaryu et al., 2025; Delfino and Espinosa, 2025; Friebel et al., 2022; Hoffman and Tadelis, 2021).

Third, we contribute to the literature on continuous improvement and the productivity gains from soliciting workers' operational knowledge (Adhvaryu et al., 2023; Ichniowski et al., 1997). A substantial share of the reports generated under the incentivized treatment concerned production conditions, and the associated productivity gains suggest that workers hold decentralized information about operational problems that the organization can act on once it is structured to elicit and respond to it. Our results provide experimental evidence that aligning managerial incentives is what activates this channel, connecting the returns to worker voice to the bottom-up problem-solving emphasized in this literature.

2 Background

2.1 Grievance Redressal in Indian Garment Firms

Wages and working conditions in India's textile sector regularly draw the attention – and often the concern – of multinational buyers, government officials, and labor rights organizations (Boudreau, 2024). Firms use a variety of managerial tools to address these concerns, including the formation of worker committees, suggestion boxes for grievance redressal, and the development of multi-function organizational development teams. The effectiveness of these mechanisms, however, is generally perceived to be low: employees fear retribution by management (and have related concerns about anonymity); there are no communication channels for employers to iterate or update employees on progress in dealing with feedback; and there is often little flexibility about where and when a worker can lodge a complaint. The so-called "Due Diligence Directive" legislation passed by the European Union aims to address these gaps by mandating that suppliers of EU-based companies institute stronger systems for, among other things, incorporating worker feedback and appropriately responding to worker concerns. It remains to be seen whether these mandates will find purchase.

2.2 Inache: a two-way anonymous communication technology

To address workers' and firms' needs for better communication and reporting, GBL designed a technology platform, called Inache, that enables frontline workers to better communicate with management. We partnered with GBL and Shahi Exports, Private Limited, the largest garment manufacturing firm in India, to launch Inache in Shahi's factories in two phases: the first in November 2019 and the second in February 2020. Designed to prioritize ease of use, Inache allows workers to communicate with management via a text message or a voice note (for workers with limited reading or writing) to a dedicated contact helpline for each factory. When a worker submits a grievance, it registers on a dedicated HR administrator portal as an anonymous complaint or suggestion. The HR personnel then allocates the grievance to a designated point of contact (POC) within the HR team. Inache allows for two-way communication; the POC can, for example, request further details or clarification from the worker, and the worker can respond while maintaining their anonymity. Once the investigation is concluded, the POC updates the portal with any actions taken or decisions reached regarding the case, which are then automatically conveyed to the worker.

From the tool's first roll-out in November 2019 to the end of the study in June 2021, workers used Inache to submit a total of 830 grievances, summarized in Appendix Table A3. Cases categorized under Work Culture and Conflicts (e.g., complaints about supervisors using abusive language or requiring long hours of work) were the most common. The second most common category was Salary, Retirement, and Insurance, which included cases submitted by workers who had not yet received their bonuses or who were leaving the firm and had questions about settling their dues. Under Workplace Policies and Amenities, there were questions about leave and welfare schemes, as well as complaints about canteen food. Finally, the Production Conditions category included a range of complaints about broken equipment or uncomfortable working conditions. For example, many workers complained about high temperatures, either requesting for fans to be fixed or brought in.

Inache also had a broadcast feature, which Shahi used repeatedly during the COVID-19 pandemic (which overlaps with our study period) to send workers information about factory closures and re-openings, as well as other guidelines and safety recommendations. In addition to the above utilities, the tool also enabled the HR department to monitor its efficiency in grievance redressal, by generating reports about various performance indicators, such as the average time taken to resolve grievances and the percentage of grievances re-opened. Shahi did not keep a record of these statistics prior to the introduction of Inache.

2.3 Performance Incentives for HR

In addition to evaluating the impacts of the tool itself, a key research goal was to explore whether the tool's effectiveness varies based on the incentives facing HR personnel handling grievance redressal. To allow for this, a subset of Inache factories was chosen at random to implement a new HR incentive scheme.

In June 2020, HR personnel in these factories began receiving monthly rewards based on their performance in grievance redressal through Inache. Rewards included recognition in the form of trophies, T-shirts, coffee mugs, and other prizes. Incentives were team-based, that is, based on the entire grievance redressal team's performance. Summarized in detail in Appendix section B, the criteria were based on several metrics: promptness of initial case report filing, promptness of initial case allocation, promptness of first response to employee, the duration of the entire grievance redressal process, and the quality of the HR response (based on an external evaluator).

3 Experiment

To evaluate the effectiveness of the Inache tool and the role of HR incentives, we conducted a randomized controlled trial.

3.1 Randomization

The study sample consisted of all of Shahi's southern Indian factories. In August of 2019, we randomly assigned 43 factories to one of the three groups: tool-only (T1), tool-plus-incentives (T2), or control (C). Shahi Exports divides its operations into three divisions, which operate as independent business units. These are Men's and Boys (MnB), Ladies Style Division (LSD) and Knits. We stratified the factories by these business units for randomization.[1]

3.2 Inache Intervention

The Inache tool was introduced in Shahi factories in two phases. In the first phase (November 2019), 14 factories received the tool. In the second phase (February 2020), the remainder of the 14 units received the tool.[2] The process involved a ceremonial launch of the Inache helpline in each factory, which was attended by upper-level management along with the HR and production line workers in that factory.

For each phase, the HR department was first trained to use the tool, and the workers were trained a few weeks later. Workers were trained in batches and were shown a 15-minute presentation on the various features of the tool. This was followed by a live demonstration in which a

[1]By December 2019, just after the initial roll-out of the tool (but before the beginning of the incentive program), two T1 units had closed and their workers moved into two different T2 units. We switched one of the surviving T1 units to the T2 group to maintain balance before the incentives were rolled out. This left a total of 41 units in our sample, 26 that received the tool, 13 of which also received incentives. Two additional units were closed around the beginning of July 2020 but they are included in most of our analysis.

[2]While asking for nominations from factories, only 14 had sufficient manpower to handle the Inache grievance redressal process – from allocating complaints to giving updates and resolving issues. The remaining factories required time to hire new staff for the Inache helpline.

worker from the training group was selected to send a greeting text or voice note on the helpline number. The HR personnel present at the training would then show how the grievance appeared anonymously on their portal. Following the training of all the production line workers, posters in multiple regional languages were placed at all major areas of the factory (canteen, stairs, shop floor, etc), illustrating the helpline number and how the process of Inache grievance redressal works. Additionally, stickers with Inache helpline number were attached to the backs of all worker ID cards to ensure quick access to the tool.

To promote awareness, management used the central public announcement system on each factory's premises to periodically remind workers about the tool and its features. Shahi management also occasionally used the tool to broadcast information via text message to all workers using the database's mobile numbers. For example, on August 15, 2020 – Indian Independence Day – a broadcast message reminded workers to practice social distancing and use Inache for any grievances or suggestions. The text that was broadcast stated: "We wish you a Happy Independence Day. You can share your grievances or suggestions by calling or messaging on Inache No. XXXX- Shahi Management." A subset of factories (5 in T1 and 3 in T2) also sent a message during the COVID-19 lockdown in April 2020: "Message from Shahi: Hope you all are safe and healthy. Wash your hands and practice social distancing to protect yourself and others. Shahi is committed to your well-being. All Government guidelines will be followed and full wages will be paid during the lockdown period."

3.3 HR Performance Incentive Intervention

Starting in June 2020 (after the lifting of initial COVID-19 lockdown restrictions in India), we introduced a monthly incentive system for the 14 factories in the T2 (tool + incentive) group. The process involved additional training of the HR department in categorizing grievances, understanding their benchmark timelines to resolve them and how best to utilize the monthly reports generated by the tool's monitoring system to provide the team with feedback for process improvement. Monthly awards ceremonies were organized in the factories that met the incentive criteria.

3.4 Timeline

Figure 1 summarizes the main events described above, along with the timing of a baseline, midline, and endline survey, which are described in more detail in section 4.2. Shahi Exports rolled out the tool in control units in July 2021, which we use as the end date for our experiment.

4 Data

4.1 Administrative Data

As part of its normal business operations, Shahi Exports collects administrative data on worker characteristics (age, gender, educational attainment, and skill level), start and quit dates, attendance, salary, and line-level productivity, which we have used to generate our attrition, attendance, salary, and productivity outcome variables of interest.

For attrition, attendance, and salary, our sample consists of all workers employed by Shahi as of November 30, 2019 (approximately 76,000 workers). Daily productivity data is recorded at the line level. Our sample consists of all production lines operating in Shahi as of November 30, 2019 (approximately 600). To drop outliers in productivity data (likely due to reporting error), we trim at the 1^{st} and 99^{th} percentiles of the raw productivity measure.

We also have access to limited administrative data related to the worker voice tool. We have the date and category of each case filed through the tool, from November 2019 to June 2021. We also have HR performance statistics for both treatment groups (even though these were only used to determine rewards for the incentive group). For each factory month, we know the share of cases for which each criterion (prompt initial report, prompt case allocation, prompt first response, timely grievance resolution, and quality) was satisfied. Unfortunately, due to timestamp errors that were fixed in June 2020, accurate information is only available starting in July 2020.

4.2 Survey Data

In addition to the administrative data, we conducted three repeated cross-sectional surveys, randomly selecting 36 workers from each factory each time, to collect data on the following outcomes: worker perceptions of HR, workplace satisfaction, attitudes toward reporting issues, individual worker satisfaction, and worker loyalty. The baseline surveys were conducted in person in early November 2019, the midline surveys were conducted between November and February 2021 over the phone, and the endline surveys were conducted between April and June of 2021 over the phone.

We construct a management perception index, workplace satisfaction index, reporting index, personal satisfaction index, and loyalty index. Each variable is constructed by combining responses to several related questions, to which workers were asked to respond using a 3-point likert scale or a binary yes/no response. We normalize each response within a category to have a mean of zero and standard deviation of one, and average across all questions in the category.

For perception of management, we asked the workers how aware they felt the management was about the issues workers faced, with responses ranging from 1 (never aware) to 3 (fully aware). Similarly, workplace satisfaction was measured using survey responses to questions about workplace cleanliness, their commute to work, and factory conditions, among others, with responses once again ranging from 1 (unsatisfied) to 3 (satisfied). For attitudes toward reporting issues, we asked the workers if they feel comfortable reporting issues to management (yes/no) and if they (or a friend) have ever experienced negative repercussions from reporting grievances (yes/no). For individual worker satisfaction, we asked questions pertaining to work-life balance, personal satisfaction, and mental health, with responses once again on a 3-point likert scale. To capture loyalty, we directly ask workers if they feel loyalty towards and pride about working for Shahi (responses on a 3-point likert scale).[3]

[3] We also ask more indirect questions related to loyalty: if workers search for jobs outside of Shahi, if they ever make deliberate errors when unhappy at work, and whether they ever request to be transferred. When we repeat our analysis including these questions into the loyalty index, results remain the same.

4.3 Summary Statistics

Table A1 reports summary statistics of worker characteristics and factory-level productivity. There are no statistically significant differences between TI and control units, or T2 and control units, in terms of female shares, average age, average tenure, or worker skill.[4] Approximately 77% of workers are women. The average factory worker is around 32 years old, has approximately 3.4 years of experience at Shahi, and has obtained 10 years of schooling. Average schooling is lower in the tool-only group than the control group; this difference is significant at the 10% level though small in magnitude – only 0.25 years. We also report monthly absenteeism, monthly pay, and daily factory-level productivity, averaged across the six months prior to the first tool rollout (June to November 2019). None are significantly different across the three groups. We also report means of the indices from the baseline survey: management perception, workplace satisfaction, reporting, personal satisfaction, and loyalty. There are no significant differences between the control and treatment groups.

5 Empirical Strategy

In this section, we describe the regression specifications for attrition, absenteeism, salary, productivity, and our set of survey outcomes. For all five categories of outcomes, we estimate the effect of the tool and the additional effect of the incentive program. To do this, we define two indicator variables: $Tool_{jt}$ is equal to 1 if the tool is available in factory j at time t, and $Incentive_{jt}$ is an indicator variable equal to 1 if the incentive program is in place in factory j at time t. For those in T1 and T2, $Tool_{jt} = 1$ for all time periods after the roll-out of the tool in their respective factories (November 2019 for phase 1 and February 2020 for phase 2). Those in T2 additionally have $Incentive_{jt} = 1$ starting from June 2020.

[4] Shahi collects data on skill levels of its workers and categorises them broadly into highly skilled, skilled, semi-skilled or unskilled. For our analysis, we consider a worker as skilled if their skill level is highly skilled or skilled.

The regressions all have the same structure:

$$Y_{ijt} = \beta_T Tool_{jt} + \beta_I Incentive_{jt} + \gamma_1 X1_j + \gamma_2 X2_{it} + \epsilon_{ijt}, \tag{1}$$

where Y_{ijt} represents the outcome of interest in individual i, unit j, and time period t. $X1_j$ includes treatment group dummies, phase dummies, and division dummies. $X2_{it}$ is a vector of time fixed effects and individual controls (where relevant). The precise definitions of i, t, and $X2_{it}$, along with sample restrictions and weighting procedures, vary across outcomes, and we describe these details for each outcome of interest below. β_T provides the effect of the tool alone, and β_I provides the differential impact due to the HR incentives. The sum of the two provides the total effect of the tool-plus-incentives package. In all regressions, we cluster standard errors at the unit level.

While the basic structure of the regressions is the same across outcomes, the exact specification varies depending on the outcome variable because of differences in the underlying data. Table A2 provides a comparison of these details: the definition of i, j, and t, the months included in the regression, the variables making up the $X2_{it}$ vector, and the weighting procedure used. We highlight the important points and differences in the text below.

To examine attrition, we calculate monthly quit rates for each unit: the share of unit j that had quit by the end of month t (out of all workers working at unit j at the beginning of the month).[5] This is the only outcome that is examined at the unit level, dropping the i subscript. Absenteeism (share of total work days a worker was absent) and salary (take-home pay, including overtime pay and bonuses) are measured for each worker i in unit j and month t. Productivity is calculated for line i in unit j on day t, as the ratio of actual pieces produced to the target number of pieces. For all of these outcomes, we have panel data – either a panel of units (for attrition), workers (for absenteeism and salary), or production lines (for productivity). In contrast, our

[5]This is different from the Cox proportional hazard model, used in previous work examining quit rates at Shahi (Adhvaryu et al., 2026, 2022), that we specified in our pre-analysis plan. We decided to take this discrete time approach after examining data on quit rates during the COVID-19 pandemic: large discontinuous jumps in quitting (e.g., in April and July 2020 for many units) suggested it would be unlikely for the required proportional hazard assumption to hold in this context.

survey outcomes (measured for worker i in unit t and survey wave t – either baseline, midline, or endline) come from a repeated cross-section of workers. All survey outcome variables are indices generated by normalizing each component of the index to mean zero and standard deviation one, and then averaging across all components.

For our administrative outcomes, we use data from June 2019 to June 2021: six months before the beginning of the experiment to the end of the experiment. Because we require data from the following month to accurately calculate quit rates for a given month, our attrition regressions only make use of quit rates until May 2021. Survey outcomes are only available from the three points of time captured by the baseline, midline, and endline surveys.

Due to COVID-19 restrictions, all factories closed for a period from mid-March to mid-May 2020 and then again for all of May 2021. There was some variation across factories in closure dates, as well as in the way they recorded attendance and salary in the administrative data during these dates. We therefore drop a fixed closure period from all absenteeism and salary regressions. To account for potential reporting error in factory closure dates, we define the closure period to be the same for all factories: from March 23 (the earliest reported closure date) to May 24 (the latest reported reopening date) in 2020 and May 1 to June 6 in 2021.[6] Because productivity measurements are missing on days when a particular line was not operating, we do not impose an additional restriction on the productivity regressions, but we show robustness to dropping the same months that are dropped from the absenteeism and salary data (April 2020 and May 2021).

The vector of control variables $X2_{it}$ includes a set of time dummies, which depend the whether outcomes are measured at the month, day, or survey wave level. For worker-level outcomes, $X2_{it}$ also contains the following demographic controls: gender, age category, tenure category, and education category dummies. For absenteeism and salary, observing the outcome is conditional on the worker still being employed at the factory. We therefore use dynamic inverse probability weighting, where each observation is weighted by the inverse of the predicted probability of still being employed by the firm in a particular month (predicted using the time-invariant covariates

[6] There were some discrepancies between the attendance data and stated closure dates for some factories.

in $X1_{ijt}$ and $X2_{it}$, based on separate regressions for each month).

6 Results

The central pattern of our findings is as follows: the communication tool did little on its own, but once paired with incentives for HR managers to respond, it produced economically meaningful gains in attendance, earnings, and productivity. None of the benefits of the tool materialized in the absence of these incentives. We document this pattern first in the administrative outcomes, then in workers' survey responses, and finally trace it to the changes in organizational behavior – greater HR responsiveness and increased worker reporting – that distinguishes the two treatment arms.

6.1 Quit Rate, Absenteeism, Salary, and Productivity

Table 1 reports the administrative outcomes. The same pattern recurs across all four: the tool on its own has no discernible treatment effects, while the addition of HR incentives moves each outcome toward improved firm performance.

In the quit rate regressions in column 1, the tool coefficient is positive and the incentive coefficient is negative, though neither is individually significant. The total effect of the combined package implies a reduction in turnover of about 6 percent relative to control. While imprecise, this estimate is sizable and in the expected direction.[7]

For absenteeism in column 2, the tool by itself again has no significant effect, but both the incentive interaction term and the total effect of the combined package are negative and statistically significant. When paired with HR incentives, the tool reduced absenteeism by 1 percentage point, which is approximately 13 percent of mean absenteeism in the control group, significantly different from the null effect of the tool alone. Because salary is closely tied to

[7]Quit rate variation was likely particularly vulnerable to the Covid-19 pandemic's shock to the macro environment, as our intervention period overlapped with several work stoppages and quarantines, in addition to the uncertainty the pandemic introduced. These aggregate fluctuations possibly overwhelmed any treatment-induced variation, resulting in diminished precision in treatment effect estimates.

attendance, the salary results mirror those for absenteeism: the combined package raised salary by over 3 percent, whereas the tool alone did not.

The pattern is identical for productivity, which is the largest driver of profit in this setting. The tool alone had no significant effect; however, the additional effect of the incentives was positive and statistically significant, with a magnitude of 3.7 percentage points, or nearly 7 percent relative to the control group mean. The combined tool and incentive package generated a 2.5 percentage point improvement in productivity (significant at the 10 percent level) amounting to about 5 percent of control group mean productivity. In sum, identical voice-enabling technology, available in both treatment arms, raised productivity only when managers were incentivized to act on what it surfaced.

Our results are robust to various sample restrictions and alternative specifications. In column 1 of Table A4, our quit rate results look similar when we drop April 2020 and May 2021, the months missing for our remaining administrative outcomes due to factory closures. The near-identical estimates across the two specifications alleviate concerns that large increases in quit rates during those months, had they been concentrated in one treatment arm, could be biasing our estimates of β_T and β_I, though the broader pandemic uncertainty likely dampened the treatment's impact on this outcome in general. In columns 2 and 4, the absenteeism and salary results are robust to dropping the demographic controls. In columns 3 and 5, they are also robust to dropping May 2020, in addition to April 2020 and May 2021, because the factory was closed for half of that month. For productivity, we report regressions that drop any remaining production days in April 2020 and May 2021, for consistency with the absenteeism and salary regressions, and results are almost identical (column 6).

6.2 Survey Outcomes

The survey outcomes in Table 2 offer a first indication of why the combined package worked. We find no statistically significant effect of either intervention on workers' perception of management, satisfaction with workplace conditions, individual satisfaction, or loyalty. We do, however, find that the addition of HR incentives yields a significantly larger effect on workers' confidence reporting issues to management than the tool alone: the *Incentive* coefficient of 0.32 is significant at the 5 percent level. The combined effect of the tool and incentives is positive, a 0.15 standard deviation increase over the control group, though not statistically significant. This pattern echoes what we observed for absenteeism, salary, and productivity, and points to workers' willingness to report as a candidate channel. Indeed, while the coefficients in the remaining regressions are not individually significant, all but one (workplace conditions) display the same structure: negative or small positive *Tool* coefficients alongside positive *Incentive* coefficients. Worker voice, in other words, appears to strengthen when HR managers have incentives to address suggestions and grievances in a timely and appropriate manner.

6.3 Role of Incentives

If the tool generated returns only when paired with incentives, the natural question is what the incentives changed inside the organization. Figure 2 addresses this directly, first by examining how the incentives affected HR performance, the actual effectiveness of the worker voice system, and then by examining how they affected worker reporting behavior, which should respond to workers' perception of that effectiveness.

Panel A of Figure 2 reports, separately for each treatment group and criterion, the average share of cases in a given factory and month satisfying each of the incentive criteria: initial case filing within one day of report, allocation to a manager within one day of filing, first response to the worker within one day of allocation, timely resolution from start to finish, and quality deemed appropriate by an external evaluator. The incentive group was substantially more timely than the tool-only group in both the case allocation stage and in total resolution time. The share of cases satisfying the total resolution time criterion was 16 percentage points, or almost 50 percent, higher in the incentive group than in the tool-only group. Notably, the rate of satisfying the quality criterion was similar, and very high, in both groups: incentivized HR teams resolved cases faster without sacrificing quality.

Next, we ask whether this faster resolution without diminished quality resulted in workers using the tool more or differently. Panel B of Figure 2 plots the cumulative number of cases by treatment group from November 2019 to June 2021. The number of grievances received rose far more steeply in the incentive factories than in the tool-only factories, with the gap opening just after the launch of the incentives and widening thereafter.

We formalize this comparison by estimating the following regression, restricting to the two treatment groups, since grievance case counts are not available for the control group:

$$G_{jt} = \beta_I Incentive_{jt} + \gamma_1 X1_j + \gamma_2 X2_{jt} + \epsilon_{ijt}, \tag{2}$$

where G_{jt} is the number of grievances in a particular category in unit j in month t, $Incentive_{jt}$ and $X1_j$ are defined as above, and $X2_{jt}$ contains year and month fixed effects.

In Table 3, the incentive coefficient is positive across all four grievance categories. In columns 1 and 4 it is significant at the 10 percent level: incentivized factories saw significantly more cases related to salary, retirement, and insurance, as well as to production conditions. The production conditions result is the most striking, with a coefficient almost double the control group mean. Communications in this category spanned factory temperature, machine maintenance, personal protective equipment, drinking water, and shop floor cleanliness.

This last result speaks to a distinctive feature of our findings. Previous work in this setting has documented reductions in absenteeism from enhanced worker voice (Adhvaryu et al., 2026, 2022), but ours is the first to document gains in productivity, which are driven by the combination of the voice tool and HR incentives that prior studies did not test. Because the incentives led workers to file more cases concerning production conditions, effective responses to those cases are a plausible source of productivity benefits. A large literature establishes that worker productivity falls with high heat (Adhvaryu et al., 2020; LoPalo, 2023; Zhang et al., 2018), and many of the cases submitted to Inache reported high temperatures or requested the repair or addition of fans. Recent work has further documented the productivity benefits of workers reporting production-related problems to management (Adhvaryu et al., 2023), and the importance of manager-worker cooperation in making the operational adjustments that raise productivity (Adhvaryu et al., 2025).

7 Conclusion

This paper provides experimental evidence that the returns to a workplace technology depend on whether organizational incentives are aligned to act on what it enables. In a factory-based randomized controlled trial, we gave units access to an anonymous worker-management communication tool, either alone or paired with incentives for HR managers to resolve grievances promptly and appropriately. The tool by itself had little effect on workplace outcomes. Paired with HR incentives, it reduced absenteeism, raised worker earnings, and increased productivity. Because the technology was identical across the two treatment arms, the contrast isolates organizational responsiveness, rather than access to the technology, as the binding input.

The mechanism evidence points to the same conclusion. Incentivized HR teams resolved cases more quickly without sacrificing quality, and workers in turn reported more issues and grew more confident in doing so, particularly issues bearing on production conditions. Previous interventions to strengthen worker voice in similar settings have not generated productivity gains; that ours does, only under the incentivized treatment, suggests that motivating the organization to respond is what converts enhanced voice into measurable performance improvements.

More broadly, our findings speak to a long-standing puzzle: why firms so often fail to capture the returns to technologies that should raise productivity. The answer, at least in our setting, lies less in the technology than in the organization around it. Technologies that depend on human response deliver their potential only when the incentives of those who must respond are aligned to do so. Investments in technology that neglect this complementary margin may fall well short of their promise.

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Tables and Figures

Figure 1: Study Timeline

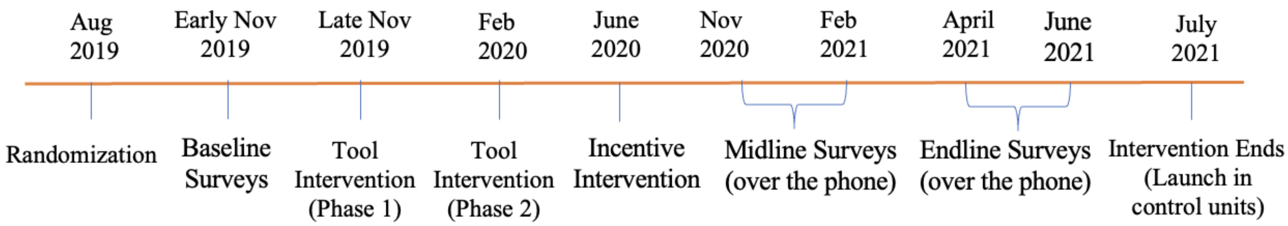


Table 1: Effects of Tool and HR Incentives on Administrative Outcomes

	(1) Quit Share	(2) Absenteeism	(3) Log(Pay)	(4) Productivity
Tool	0.0026	-0.00023	-0.00067	-0.012
	(0.0033)	(0.0036)	(0.011)	(0.014)
Incentive	-0.0062	-0.0099**	0.033**	0.037**
	(0.0038)	(0.0044)	(0.013)	(0.018)
Observations	940	1,043,952	1,039,503	344,781
Control Mean Outcome	0.067	0.079	8.96	0.53
Tool + Incentive	-0.0040	-0.010	0.032	0.025
Tool + Incentive p-val	0.471	0.045**	0.069*	0.078*

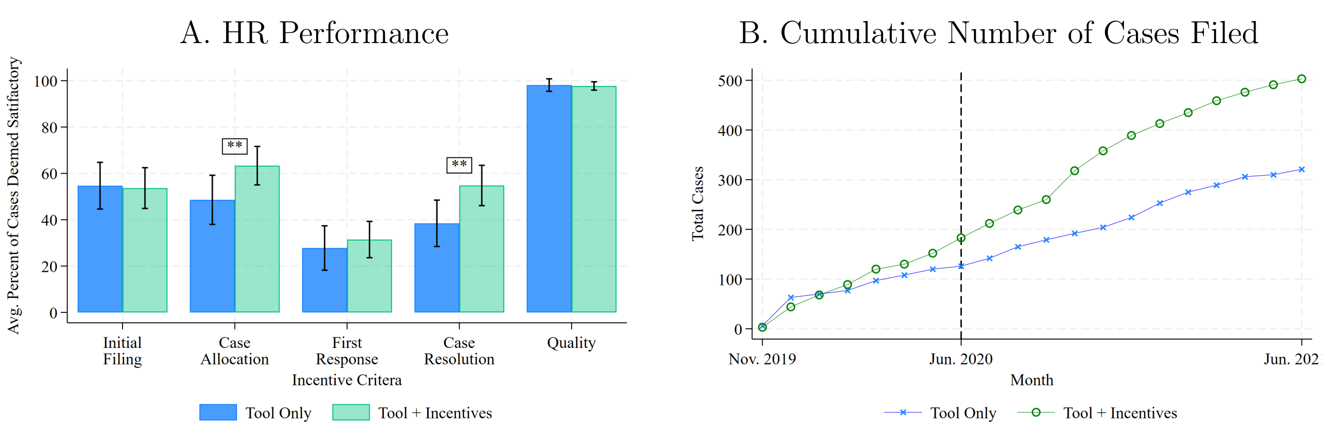
Notes: Standard errors, clustered at the unit level, in parentheses (* p< 0.1 ** p< 0.05 *** p< 0.01). Details of each regression described in section 5 and Table A2. All regressions control for year, month, treatment group, phase, and division fixed effects.

Table 2: Effects on Survey Outcomes

	(1) Perception of Management	(2) Workplace Conditions	(3) Confidence Reporting Issues	(4) Individual Satisfaction	(5) Loyalty
Tool	-0.092	0.027	-0.17	0.033	0.059
	(0.14)	(0.13)	(0.11)	(0.12)	(0.20)
Incentive	0.013	-0.065	0.32**	0.071	0.13
	(0.16)	(0.12)	(0.15)	(0.099)	(0.16)
Observations	3926	3926	3926	3926	3926
Control Mean Outcome	0.008	0.000	-0.019	0.059	0.066
Tool + Incentive	-0.079	-0.038	0.150	0.103	0.187
Tool + Incentive p-value	0.656	0.731	0.399	0.410	0.344
Controls	Demographic	Demographic	Demographic	Demographic	Demographic

Notes: Standard errors, clustered at the unit level, in parentheses (* p< 0.1 ** p< 0.05 *** p< 0.01). Regressions use three repeated cross-sectional surveys administered to a random sample of workers. All regressions control for survey round, treatment group, phase, and division fixed effects. "Demographic" controls include education, age, skill, and experience category fixed effects.

Figure 2: HR Performance and Number of Cases by Treatment Group



Notes: Both graphs use factory-month-level data. Panel A uses data from July 2020 (the first month of accurate HR performance statistics) to June 2021. Error bars represent 95% confidence intervals and asterisks indicate significant differences between the two groups (* p< 0.1 ** p< 0.05 *** p< 0.01). In panel B, the dashed vertical line marks the beginning of the HR incentive program in the incentive units.

Table 3: Effect of Incentives on Number of Cases

	(1) Salary, Retirement, Insurance	(2) Work Culture & Conflicts	(3) Workplace Policies & Amenities	(4) Production Conditions
Incentive	0.34*	0.01	0.03	0.28*
	(0.19)	(0.27)	(0.20)	(0.15)
Observations	480	480	480	480
Control Mean Outcome	0.33	0.60	0.26	0.15

Notes: Standard errors, clustered at the unit level, in parentheses (* p< 0.1 ** p< 0.05 *** p< 0.01). Regressions include unit-months during the time period the tool was in operation (November 2019 to June 2021). All regressions control for year, month, treatment group, phase, and division fixed effects.

A Additional Tables and Figures

Table A1: Summary Statistics

	(1) Control Mean (SD)	(2) Tool-Control Difference (SE)	(3) Incentive - Control Difference (SE)
Female	0.77	0.02	-0.03
	(0.42)	(0.05)	(0.05)
Age	32.31	0.03	-0.41
	(8.14)	(0.57)	(0.73)
Tenure	3.42	0.01	-0.26
	(2.07)	(0.19)	(0.25)
Skilled	0.14	-0.00	0.02
	(0.35)	(0.03)	(0.03)
Years of Schooling	9.98	-0.25*	-0.19
	(2.33)	(0.13)	(0.17)
Pre-Treatment Absenteeism	0.07	-0.00	0.00
	(0.07)	(0.01)	(0.00)
Pre-Treatment Pay	8090.55	21.56	355.56
	(3284.66)	(425.48)	(385.60)
Pre-Treatment Productivity	0.48	0.02	-0.03
	(0.09)	(0.03)	(0.03)
Management Perception Index	-0.06	0.09	0.08
	(1.04)	(0.12)	(0.14)
Workplace Satisfaction Index	0.02	-0.03	-0.04
	(1.00)	(0.12)	(0.11)
Reporting Index	0.04	0.06	-0.18
	(0.91)	(0.12)	(0.17)
Personal Satisfaction Index	0.02	0.06	-0.08
	(1.00)	(0.10)	(0.09)
Loyalty Index	0.07	-0.09	-0.11
	(1.04)	(0.16)	(0.14)
Number of factories	15	13	13

Notes: Columns 2 and 3 report the difference between the control group and each treatment group, along with standard errors clustered at the factory level in parentheses (* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$). With the exception of productivity, which is averaged to the factory level, all variables are at the individual worker level. Pre-treatment absenteeism and pre-treatment pay are monthly measures averaged from June to November 2019 for each worker. Pre-treatment productivity is daily productivity averaged from June to November 2019 for each factory. All index variables are obtained from the baseline survey, conducted in November 2019, of 36 workers per factory.

Table A2: Variable Definitions and Regression Details

Outcome	Variable definition	Time frame	$X2_{ijt}$	Weighting	Structure and Sample
Attrition	Share of workers that quit in unit j and month t	June 2019 to May 2021	month and year dummies	None	Panel of all units in study
Absenteeism	Share of days working days absent for worker i in unit j and month t	June 2019 to June 2021 (excluding April 2020, May 2021)	month and year dummies; demographic controls	inverse probability weights	Panel of all workers employed by Shahi as of November 30, 2019
Salary	Log of take-home pay, including bonuses and overtime, for worker i in unit j and month t	June 2019 to June 2021 (excluding April 2020, May 2021)	month and year dummies; demographic controls	inverse probability weights	Panel of all workers employed by Shahi as of November 30, 2019
Productivity	Ratio of actual pieces produced to target number of pieces for line i in unit j on day t	June 2019 to June 2021 (excluding days with no production)	month, year, day of month, and day of week dummies, demographic controls	none	Panel of all lines operating as of the last week of November, 2019
Survey outcomes	Standardized indices of survey responses for worker i in unit j and survey wave t	November 2019, November-February 2021, April - June 2021	survey wave dummies; demographic controls	none	Repeated cross-sectional random sample of survey respondents

Table A3: Number of Cases by Category

Case Category	Total Cases
Work Culture and Conflicts	320
Salary, Retirement and Insurance	286
Workplace Policies and Amenities	160
Production Conditions	64
Total Cases	830

Table A4: Robustness Checks

	(1) Quit Share	(2) Absenteeism	(3) Absenteeism	(4) Log(Pay)	(5) Log(Pay)	(6) Productivity
Tool	-0.00082	-0.00013	-0.00066	0.00049	0.0018	-0.011
	(0.0032)	(0.0036)	(0.0038)	(0.012)	(0.012)	(0.015)
Incentive	-0.0050	-0.0098**	-0.011**	0.045***	0.035***	0.036*
	(0.0045)	(0.0045)	(0.0047)	(0.014)	(0.011)	(0.019)
Observations	862	1,043,952	998,592	1,039,503	995,227	330,000
Control Mean Outcome	0.065	0.079	0.076	8.96	8.97	0.53
Tool + Incentive	-0.0060	-0.010	-0.012	0.045	0.037	0.025
Tool + Incentive p-val	0.290	0.053*	0.019**	0.014**	0.026**	0.078*
Demographic Controls	N/A	No	Yes	No	Yes	N/A
Drop Additional Months	April 2020, May 2021	None	May 2020	None	May 2020	Apr 2020, May 2021

Notes: Standard errors, clustered at the unit level, in parentheses (* p< 0.1 ** p< 0.05 *** p< 0.01). Details of each regression described in section 5 and Table A2. All regressions control for year, month, treatment group, phase, and division fixed effects. "Demographic" controls include education, age, skill, and experience category dummies.

B Reward Criteria

Factories that fulfilled all of the following criteria received the monthly incentive.

1. **Initial case report filing**: After receipt of a worker's message via the tool, the Case Reporter (CR) must have prepared a case report and assigned it to the Case Manager (CM) within 1 working day for at least 65% of cases.

2. **Case allocation**: After receipt of a report from the CR, the CM must have assigned the case to a Case Troubleshooter (CT) within 1 working day for at least 65% of all cases they receive.

3. **First response**: After receipt of assignment from the CM, the CT must have sent a first response to the worker, assigning them a case number, within 1 working day for at least 65% of cases.

4. **Grievance resolution**: The CT must have resolved the grievance within the target time (pre-specified for each category) for at least 65% of cases.

5. **Quality of response**: Quality of grievance redressal was evaluated by an external person, who reopened any cases where grievance resolution was not handled appropriately. To qualify for incentives, the rate of re-opening had to be less than 10% of all cases received. In other words, at least 90% of all cases must have been deemed to have been handled satisfactorily.[8]

Note: During the project, we received feedback from the Organization Development department regarding the Inache incentives and issues like audits, workload of Inache users and other cases where it was difficult to clear incentives, even after the highest level of efforts. Thus, starting from 1st October 2020, old cut-offs were replaced with the new ones (mentioned above). The changes were:

[8]The quality was evaluated by a staff member from the centralized Organization Development department of Shahi Exports), based on (1) the tone of the SMS response to workers, (2) the interaction between the CR, CM, and CTs in the case log, and (3) evidence uploaded on the grievance case file in the tool.

- Initial case report filing: Changed the cut-off from 90% to 65%.
- Case allocation: Changed the cut-off from 90% to 65%.
- First response: Changed the cut-off from 90% to 65%.
- Grievance resolution: Changed the cut-off from 75% to 65%.
- For Quality Checks the cut-off remained unchanged at 10% .

From June 2020 to September 2020, all the cases and calculations went as per old cut-offs. From 1st October 2020, new cut-offs came into effect.