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RESEARCH ARTICLE

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Emphasizing worker identification with skills to increase helping and productivity in production: A field experiment

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Abstract

Can productivity improve if workers identify more with the skills they use in their work environment? This paper reports the results of an experimental design that was peer-reviewed prior to collecting data. The research setting is a global manufacturer using a novel smartwatch-based system for distributing work tasks among factory floor workers. Drawing on the concepts of identification and helping in organizations, we hypothesized that fostering workers' identification with their own skills could serve as a mechanism to enhance helping behavior on the factory floor, which should improve productivity. We designed a compound skill-fostering treatment consisting of communication, meetings, and exercises regarding individual skills. We treat one large factory area for 2 weeks and keep a similar area in a sister factory as a control group for comparison in a difference-in-difference model. The results show that nudging skill identification increases workers' identification with skills, but we do not find evidence for increased helping behavior or increased productivity. Our results help develop theory around multiple sub-identities and provide guidance for future studies seeking to enhance identification in organizations.

KEYWORDS

digitalization, helping behavior, identification at work

Highlights

- A 4-week-long field intervention was conducted in a digitalized factory aiming to increase workers' identification with their skills.
- The experimental design was reviewed and accepted by the JOM Editors before data collection.
- Identification with skills increased and emotional exhaustion decreased.
- Expected positive effects of the treatment on helping behavior and productivity were not supported.
- Managers and future studies should try to disentangle identification with skills and machines.

1 | INTRODUCTION

Workers are more motivated to exert effort when they identify with their immediate work environment (Albert et al., 2000; Dutton et al., 1994). In fabrication operations, workers' identification with a set of machines often comes naturally since managers allocate workers to machines to solve two problems: detecting interruptions as soon as possible in hard-to-oversee facilities and matching technical problems with the appropriate skill. This way, a worker can closely monitor the assigned machines' status and develop appropriate skills over time. In this context, skill can be seen as the ability of a worker to operate or solve an interruption of a specific machine type. Due to the worker-machine allocation, workers naturally attach meaning to the allocated machines and incorporate them into their self-concept: they *identify* with the machines (Miscenko & Day, 2016).

Even when allocating workers to specific machines, factory floors are usually organized in teams that rely on citizenship behavior among workers, such as helping behavior (Cantor & Jin, 2019). We define helping as the voluntary exchange of work among workers that is not directly or explicitly recognized by the formal reward system (Organ, 1988). Thus, the tight allocation of the workforce to machines can be useful for monitoring large-scale production and driving identification with a few machines. However, it may crowd out the potential to identify with other features of the factory floor that could increase productivity via helping behavior. This problem becomes particularly salient after a digital transformation of the factory because digitalization can eliminate the problems that the strict allocation of workers to specific machines intended to solve; it can make all machine status digitally available and dynamically match factory floor tasks with workers' codified skills.

The inherent challenge of motivating employees to show helping behavior is relevant in various contexts, including manufacturing. Interestingly, a digital transformation can have positive and negative effects on job resources (Parker & Grote, 2022). On the one hand, new digital technologies can potentially reduce the need for human interaction and coordination. For example, algorithms can automatically allocate human workers to tasks (Bai et al., 2022). On the other hand, new digital technologies can increase the transparency on the shop floor, highlighting where problems are and automatically ping someone to help. This information is necessary but not sufficient for helping behavior and introduces the challenge to encourage helping among workers. For the past 4 years, we have studied a company that has experienced this double-edged problem first-hand: a globally operating manufacturer headquartered in Italy. The company has implemented a digital worker-task matching system using smartwatches, machine sensors, and a digital back end (see Figure 1).

The company in our research setting produces millions of complex metal parts daily, and its workers receive information about, for instance, machine interruptions from machines directly and in real-time via smartwatches in case they are available and have the appropriate codified skill in their profile. Codified skills are the binary codifications of human skills in a digital system. The new technology has changed the past organization based on machine groups into a new organization based on skills. The main goal of the system is to pool skills across machines to achieve higher productivity. The company aims to be at the forefront of digital transformation in its industry, has undergone far-reaching changes in its production organization, and faces unique behavioral challenges grounded in their progressive digital transformation. As known, profound technological changes can positively and negatively affect humans at work (Parker & Grote, 2022). Therefore, our study chooses a behavioral angle and considers workers' well-being important to an organization's social sustainability.

In theory, workers equipped with the smartwatch would no longer restrict their work to a specific area or set of machines but focus on any machine that requires their skill, as all solvable tasks appear on the smartwatch as interruptions occur (see Figure 1). In practice, however, workers have established their work identification based on machines for years, and the change of identification lags the technology change. The new technical production logic focuses on matching activities and codified skills, whereas the socio-psychological concept of identification still focuses on machines. Workers prefer to continue working on a limited set of machines since workers strongly identify with these machines. Employees are drawn to "their" machines because they are familiar with and part of their accustomed surroundings. Sociologists have described this process as processual interactions that help humans understand and construct their reality and their concept of self within that reality (Gecas, 1982). While this division of work by machines indeed also has benefits in reducing walking distances and skill-specificity, the narrow identification with and feeling of responsibility for machines may make employees reluctant to help in other areas, which is a success factor in production (Cantor & Jin, 2019). Forcing workers to work on machines outside the scope of their work identification bears the risk of upsetting workers, resulting in low satisfaction and eventually negatively impacting productivity. Instead, voluntary willingness to help is preferred.

Notably, in our research setting, the lack of helping behavior is not a temporary adoption difficulty of the

FIGURE 1 Impressions from the factory floor (left), the smartwatch (middle), and the digital front end (right).

system but has persisted since the system was introduced in 2020. Based on the theoretical and practical problem outlined above, we derive the following research question: *Can we improve helping behavior and productivity by increasing workers' identification with skills*?

The potential contribution of addressing this question to operations management theory lies in proposing a shift in worker identification as a concealed requirement for realizing the advantages of digitalization in production settings. Specifically, this study can contribute to the behavioral operations management discussion on worker identification and helping behavior. This behavioral operations literature has been silent on identification in manufacturing and instead centered on similar problems in software use and delivery contexts (Bagozzi & Dholakia, 2006; Ta et al., 2018). At the same time, the community has initiated a discussion on how helping behavior can improve operations (Cantor & Jin, 2019). Our work can broaden the discussion of identification from software and delivery to manufacturing and continue the helping behavior research by examining whether a treatment can incrementally affect workers' identification patterns to favor helping behavior and productivity. Our research builds on the concept of identification in organizations (Albert et al., 2000; Ashforth et al., 2008) and draws motivation from recent management theory around the coexistence of multiple sources of identification (Bataille & Vough, 2022)—such as machines and skills. Using this lens, we aim to draw novel operations-specific implications for helping behavior and productivity on the factory floor of a highly digitalized manufacturer. Thereby, we offer identification as a potential complement to the behavioral operations literature on how task design, interdependence, incentive systems, or motivation can contribute to worker collaboration (De Vries et al., 2016; Franke et al., 2022; Schoenherr et al., 2017; Siemsen et al., 2007).

2 | THEORETICAL BACKGROUND

2.1 | Work identification and identity

The literature on identification and identity has a long tradition but is also heterogeneous and lacks universal definitions (Albert et al., 2000; Miscenko & Day, 2016). Our study follows the idea of personal identification at the individual level of inclusiveness (Brewer, 1991; Brewer & Gardner, 1996), which argues that any collection of meanings can define a worker's self-concept at work (Gecas, 1982). Examples can be roles at work, membership in social groups, or—as in our study—one's professional skills or the machinery one uses.

Gecas (1982) summarizes two alternative views of how identification can emerge: via an individual's interactions with the environment or via the roles of an individual. Both are valid sources of identification, yet this study focuses more on how humans connect to features of their work through interactions. In line with this approach, Miscenko and Day (2016) have proposed that "identity refers to the meaning of a particular entity (i.e., role, organization) that is internalized as part of the self-concept" and that "identification is a cognitive/psychological/emotional attachment that an individual makes to a role, team, organization, or other entity" (p. 217). In other words, the former is a state, and the latter can be interpreted as a behavioral process. These definitions do not conflict with the conceptualizations of identity and identification as socially constructed (i.e., Turner & Tajfel, 1986) but are complements. We focus on personal identity since this concept commonly distinguishes individuals, whereas social identity focuses on differences between groups that can define in-groups and out-groups with their identity (Ashforth et al., 2008).

We use the term identification in our study instead of identity since workers literally seem to be attached to their machines and are reluctant to go elsewhere on the factory floor to help. Identification is a useful term in our study as the notion of identification as a process matches the reality on the factory floor: workers become attached through their work. Furthermore, this view of identification fits the idea that attachments are somewhat fluid and can be changed via management practices. However, we acknowledge that both identification and identity concepts are inextricably connected on the conceptual level (Ashforth et al., 2008), point to studies that discuss their relation (Dukerich et al., 2002; Dutton et al., 1994), and note that scholars often treated them as synonyms (Miscenko & Day, 2016). In summary, while we review the consolidated literature on identification and identity and our arguments would allow using both terms, we opt for "identification" for its stronger resonance with our research context. We review the consolidated literature on both concepts.

Identification matters in operations contexts. Scholars have examined the common identification of production workers with their production area and compared it to sports fans who identify with their team (Urda & Loch, 2013). The study showed that when a worker is unexpectedly rewarded, it may trigger guilt among other workers in that area as they start to ask why they were not good enough. However, no guilt was measured among supporters of the same sports team in a comparable situation. Thus, mechanisms and outcomes around identification are not identical in production and other settings, which motivates behavioral operations examinations. Several studies define identity and the target of identification as the social group in the operations management literature. They focus on hiring and in-group membership (Casoria et al., 2022; Del Carpio & Guadalupe, 2022), trust in transport services (Ta et al., 2018), groups making donations (Charness & Holder, 2019), or identification with buyers in supply chains (Corsten et al., 2011). Only a few operations management studies chose our focus on individual-level personal identification and on how features other than social group membership affect identification and outcomes (e.g., Reagans, 2005).

To the best of our knowledge, the behavioral operations management literature has not examined the effects of identification on the factory floor, and all prominent review articles omit the concept (Bendoly et al., 2006; Bendoly, Croson, et al., 2010; Croson et al., 2013; Donohue et al., 2020; Fahimnia et al., 2019). A recent review of the literature concludes: "it is clear that decision making in practice continues to be heavily influenced by human judgment, even with regard to highly automated and supposedly objective systems." (Fahimnia et al., 2019, p. 29). Identification is one element that may explain human judgment in decisions about whether to help or not.

2.2 | Helping behavior

To improve productivity, manufacturing relies on workers to help each other to improve overall performance (Cantor & Jin, 2019). The operations management literature has established that correctly designing incentives can encourage collaboration (e.g., De Vries et al., 2016; Siemsen et al., 2007), yet a trade-off exists between the use of explicit incentives and possible concerns of crowding out intrinsic contributions across many contexts (Deci et al., 1999). This is especially true when incentives are closely tied to performance and when quality is essential, as is commonly the case in factory floor operations (Cerasoli et al., 2014). Therefore, the literature has begun to focus on fostering voluntary worker behavior in addition to the research on incentives. In broad terms, helping behavior is part of "organizational citizenship behavior," which is defined as "individual behavior that is discretionary, not directly or explicitly recognized by the formal reward system, and that in the aggregate promotes the effective functioning of the organization" and is a synonym for altruism (Organ, 1988, p. 4). It is useful to specifically observe helping as one factor of organizational citizenship behavior in the context of operations since collaboration is immediately relevant for performance. Despite the scarce coverage of helping behavior in the operations literature, it is a relevant concept in practice, as examples from the company in our research setting can illustrate:

> When I know that a machine [of a co-worker] is not running "clean," say the [robot] arm keeps getting the alignment of the part wrong while inserting parts into the press, I will look out for tasks on his machine. I can help out when he is on break or away for some reason.

However, such helpful behavior is not given in a production context. Consistently, the team leader described a situation where helping could have avoided performance losses:

> I came in this morning, and my dashboard showed me that this machine had been interrupted for 24 minutes already. That's ridiculous! One guy is in the lab, and the other is chatting. They go "they have people over there. Not my job" although it really is. This grinds my gears.

The operations management literature has hitherto not addressed the link between personal identification and helping behavior or other types of cooperation. Previous contributions have addressed related concepts, such as the effects of within-group interactions on performance in project contexts (Bendoly, Thomas, & Capra, 2010) or functional dominance, which can reduce cooperation and affect the performance of cross-functional teams (Franke et al., 2022; Malhotra et al., 2017). Moreover, conflicts can reduce team cooperation and the performance of cross-functional teams (Franke et al., 2021; Oliva & Watson, 2011). Cantor and Jin (2019) were the first to examine questions about voluntary help in production explicitly. Their study finds that workers who are more aware of others' efforts will more likely detect performance differences and attribute them to a lack of motivation, which reduces helping behavior. The paper suggests that creating interdependence between the workers' performance can encourage helping. Interdependence is the extent to which employees depend on other group members to carry out work effectively (Bachrach et al., 2006; Van Der Vegt et al., 2003).

Interdependence is a critical factor regarding helping behavior, both in the operations and general management literature. Studies agree that interdependence can drive team collaboration by making it a necessity (Cantor & Jin, 2019; Schoenherr et al., 2017). Interdependence makes one's own success dependent on others' work. Thereby, it benefits those who help others via a self-serving element that transcends the altruistic help concept. The management literature commonly examines helping behavior and related concepts in such interdependent teams. For instance, scholars have accumulated evidence supporting that collaboration or felt obligations to help, as well as concepts that derive from them (cohesion, information exchange, etc.), drive performance in work teams (Kilcullen et al., 2022; Lorinkova & Perry, 2019; Mathieu et al., 2008; Mathieu et al., 2019; Mesmer-Magnus & DeChurch, 2009). However, not all production tasks are interdependent or can be changed to become interdependent. Unlike in assembly flow lines or cellular manufacturing, large-scale automatized and digitalized mass unit-production settings require workers to monitor production and autonomously intervene when interruptions occur rather than actively collaborating as a team. Consistently, research has shown that interdependence is an important boundary condition for conclusions around helping behavior (Bachrach et al., 2006). This study examines an under-researched, non-interdependent operational setting to help explain the scarcely understood relation between helping and productivity from an identification standpoint.

2.3 | Helping behavior and identification

The most natural conclusion from intersecting research on helping and identification is that to encourage helping within a group, it is useful to emphasize employees' identification with that group, be it their immediate work group or the entire organization (Dukerich et al., 2002; Dutton et al., 1994; Janssen & Huang, 2008; Van Der Vegt et al., 2003; Wu et al., 2016). However, although production workers may be organized in teams, the workgroup may not be a salient enough feature of their work, making it difficult for workers to identify with it. Factory floor management can face a dilemma between the lack of salient teamwork and their strong reliance on voluntary help since an enforcing mechanism like interdependence is often absent. This is commonly the case in production environments such as the one we address in this study: highly automatized and digitalized mass unit-production settings in which workers monitor and intervene but seldom actively collaborate as a team. Thus, the above-cited findings from the management literature are sound but not necessarily transferable. This illustrates a research gap at the intersection of helping behavior and identification regarding the unforeseen challenges that cutting-edge digital technology imposes in manufacturing.

Instead of identifying with the team, workers tend to develop strong identification with machines via their traditional assignment to the equipment, as motivated at the start of the paper. We acknowledge that, as any human, production workers would likely respond positively to interventions or training that build team cohesion (Chiniara & Bentein, 2018; Hu & Liden, 2015). However, the effects will unlikely persist as daily routines on the factory floor are still determined by the production technology that does not reflect active teamwork. Therefore, we propose an alternative avenue to increase helping behavior and productivity on the factory floor via identification with workers' skills.

3 | HYPOTHESIS DEVELOPMENT

3.1 | Effect of identification with skills on productivity

Employees show higher levels of motivation at work when they identify with the features of their job (Albert et al., 2000; Dutton et al., 1994). Problems in highly automatized and digitalized manufacturing are often complex and involve sophisticated machinery. Thus, these problems require motivation that makes workers focus and pay careful attention when machines are interrupted. Workers who identify more strongly with their skills focus more on the immediate task since using their skills reinforces their self-concept. Focusing on work is not a tedious exercise for them but can be a source of job satisfaction when their skills and work align, as should be the case when a digital task-allocation system matches tasks with skills (Vignoles et al., 2006).

Specifically, when workers are actively solving a machine interruption, higher identification with their skills likely enables them to recall aspects of their expertise, transfer knowledge from one problem to the next, or apply the skills they have more effectively. In other words, skills that are sources of identification for a worker are likely of higher quality and more thoroughly applied, which can positively affect several facets of productivity. It can reduce the downtime of machines and processing time of interruptions and increase the availability of machines to produce parts. It can also reduce future interruptions of the interrupted machine by contributing to more sustainable problem-solving on the factory floor, further improving productivity. Finally, higher identification can also reduce the latency of pending work tasks on the factory floor when workers respond faster to tasks that provide self-reinforcing value to them. This reduces the duration of interruptions waiting unaddressed and increases operational productivity in production. Thus, we hypothesize:

> **Hypothesis 1.** Higher levels of identification with skills will be associated with higher levels of productivity in digitalized production environments.

3.2 | Effect of identification with skills on helping behavior

We expect stronger identification with skills on the factory floor to increase productivity (Hypothesis 1). We propose that one important and hitherto overlooked mechanism on how identification with skills contributes to productivity relies on mutual helping on the factory floor. Helping behavior requires awareness of other workers, machines, tasks, or general entities around one's traditional scope of responsibilities in production (Cantor & Jin, 2019). Simply put, without being aware, one cannot make the decision to help. Identification is more than awareness; it means that individuals form a psychological relationship with an entity. For a digitalized production setting using smartwatches for task allocation, workers are made aware of opportunities to exchange work with co-workers via the watch. We argue that their choice to help depends partly on their relation to their own skills. This relation is characterized in the literature as an emotional investment that individuals make in an evaluation process (Ashforth et al., 2008; Tajfel & Turner, 1982). This leads to what Miscenko and Day (2016) call attachment to an entity of the work environment, such as one's own skills.

When workers in a production facility do not identify strongly with their skills, they naturally search for other sources to define their self-concept. These can be any entities but are unlikely the team, as teamwork is less salient in highly automated and digitalized productions. The entities that workers identify with instead may or may not encourage helping due to their inherent nature. Identifying with a part of the product spectrum, for instance, would likely focus the scope of workers' awareness—a precondition to identification—on those products and, therefore, reduce helping in times when other products are scheduled or in areas where these other products are assembled simultaneously. When workers identify with the machines in their scope of responsibilities, they focus their attention on those machines and likely feel reluctant to help when machines that they do not identify with as strongly face problems. Other examples may drive helping, too yet on average, a lack of identification with their own skills can be associated with lower levels of helping behavior compared to the inverse and clearer case.

When workers identify strongly with their skills, they also indirectly identify with all tasks on the factory floor that require these particular skills. Applying the skills in the production is a way to enact workers' identification, and any task that fits their skill profile is a potential source of self-verification. Thus, stronger identification with skills will motivate workers to apply them as often as possible to reinforce their self-concept. Research has shown that individuals draw job satisfaction from identification elements that drive self-esteem and efficacy (Vignoles et al., 2006), such as solving a production task drawing on one's own abilities. This motivation to apply skills does not distinguish between tasks that one was originally assigned and tasks that lie outside one's scope of responsibility. Instead, any completed task can provide

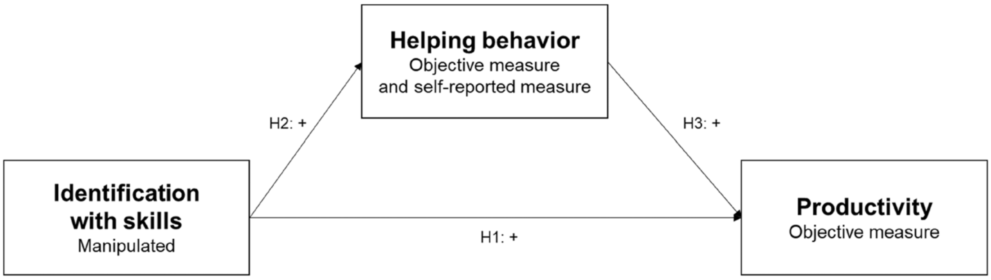

FIGURE 2 Conceptual research model. We aggregate all variable to the team and shift for analysis.

self-verification. Thus, helping others who may not have the required skills or are busy with other tasks is desirable from an identification and motivation standpoint when workers strongly identify with their production skills. Thus, we hypothesize:

> **Hypothesis 2.** Workers who strongly identify with their skills in production will show more helping behavior compared to workers who identify less with their skills.

3.3 | Effect of helping behavior on productivity

The link between helping behavior and productivity remains untested in the literature so far (Cantor & Jin, 2019). In non-interdependent operations, it is only necessary for workers to help each other when all workers with the appropriate skills for solving an open task are busy. The required information, namely the codified skill, its live availability, and the need for its application, can be made fully transparent in digitalized factories. Thus, from a utilization perspective, helping behaviors balance workload across the factory floor. Our study focuses on interruptions of semi-automated machines. Helping behavior can reduce the time a machine is interrupted and waiting for an operator. Thus, it will directly contribute to higher productivity by reducing machine downtimes and increasing unit output. Thus, we hypothesize:

> **Hypothesis 3.** Higher levels of helping behavior in automatized and digitalized production environments will be associated with higher levels of productivity.

The conceptual research model can be seen in Figure 2.

4 | METHODOLOGY

This study was pre-registered and conditionally accepted by the *Journal of Operations Management* prior to conducting the field experiment. Subsequently, we conducted the field experiment as planned and described next.

We ran a field experiment introducing an intervention that drives the identification of workers with their individual skills in a manufacturing company to stimulate helping behavior. The nature of the experimental design is a pre-post quasi field experiment. In addition to the treatment group that went through a pretest-posttest design, we simultaneously assessed a control group with no treatment using the difference-in-difference (DiD) technique. Control groups that potentially met the parallel trends assumption (i.e., have a similar pretreatment productivity trajectory) were available within the same plant and in three other plants of the company. The company led the selection of the treatment group and the treatment design. In this process, the research team ensured a stratified random sample selection and that an appropriate control group was selected by testing the parallel trends assumption of the DiD design.

4.1 | Experimental setting

The collaborating company is a large supplier and developer of metallurgy parts for automobiles, aerospace equipment, and consumer applications. Simply put, metallurgy uses pressing and thermal treatment to bring metal into shape, which allows the creation of more complex geometries than any chipping processes like lathing or milling would allow. The company produces millions of parts daily, has several thousands of customers worldwide, and employs thousands of employees in an extensive network of plants worldwide. The company provided full access to its facilities and the digital systems to allow the implementation of the field experiment.

4.2 | Experimental treatment

The treatment took advantage of the worker-task matching system using smartwatches. The system offers tasks to workers via a list that workers can choose from (see Figure 1). Importantly, the list is individualized such that only those workers who have the required codified skills see a specific task. To enable this, all skills are codified in a matrix that features all available tasks on one dimension and all anonymous worker IDs on the other dimension. The tasks are differentiated by various machine types to make sure that only workers who know a particular machine type will work on its interruptions. The "skill matrix" is a part of the back-end system and is not visible or salient to workers. The main authority to change the skill matrix is with the team leaders. For that reason and due to their intangible nature, skills and their digital codifications are an arguably less salient feature of the factory floor today.

The treatment addressed this lack of presence on the factory floor by introducing "skill weeks." The company occasionally promotes special themes that feature communication to raise awareness or workshops and training. During a recent safety week, for example, workers were motivated to report safety hazards, could order new safety shoes, and participated in first aid training. "Skill weeks" encouraged the reflection on individuals' skills in several ways: first, banners and posters made the initiative visible and transported the goal to raise awareness of how important workers' skills are to the factory. Second, workers participated in voluntary meetings that encouraged exploring, reviewing, and reflecting upon skills and their digital codifications in the skill matrix. These sessions lasted between 10 and 15 min and encouraged workers to reflect on what skills they possess, which ones are important, which ones constitute bottlenecks, or possible training needs they may have. This was accomplished by letting workers map their individual skills and development trajectories. The script of the meetings is shown in Appendix A. Third, workers received information about their skill use in real-time via their smartwatches, similar to micro-interventions in the medical sciences (e.g., Baumel et al., 2020; Fuller-Tyszkiewicz et al., 2019). Messages displayed via the watch included information on the most frequently used skills of the current and previous shifts. Figure B1 shows an example of how the message was displayed on workers' smartwatches. This combination of activities is typical for a themed week at the company and all directly address workers' skills. The company agreed to hold the "skill weeks" for 2 weeks to increase the chance of change in the identification of workers.

The treatment focused on emphasizing skills, and skills are defined by the type of machine that a worker can operate and troubleshoot. This natural connection between skill and machine type is inherent to the production system, if not to any production that operates several machines of the same type. Our study acknowledges this inherent connection, but the treatment did not emphasize it since we want to increase identification with skills, not machines. Thus, the treatment avoided making references to machines (see Appendix A and Figure B1) but focused on skills instead. In other words, our treatment focused on identifying with the skill that fits a whole set of machines instead of only a few. It thus included the potential to broaden a worker's action radius in the factory to enhance broader collaboration among workers. We expected that the treatment would strengthen the cognitive and emotional attachment that workers make to their own skills, thus, their identification with skills (Ashforth et al., 2008; Miscenko & Day, 2016). The manipulation was unobtrusive as it neither directly concerns helping behavior nor productivity. We adopted the definition of altruistic helping behavior grounded in the idea of voluntary, not mandated, helping behavior (Cantor & Jin, 2019; Organ, 1988). Therefore, the treatment did not introduce a new policy or incentive that explicitly or implicitly enforces helping.

4.3 | Manipulation check

We use several sources of information to verify that workers have experienced the treatment. First, we assessed the attendance of workers in group sessions targeted at discussing skills. Only one worker chose not to attend one of the 12 sessions. Second, we questioned workers on whether they had noticed and read banners or posters announcing the treatment and initiatives that were part of it. Most workers noticed the banners. Finally, we conducted a manipulation check (i.e., if the intervention induces a change in skill identification) using a survey question measuring how strongly workers identify with their skills at work (see Appendix C). We report a significant increase in the scale instrument as part of the results.

4.4 | Sample and pre-test survey

The sample comprises workers in a production area of the company that performs the pressing process of small metal components. The entire production process includes forming, calibrating, and thermal treatment. We focus on the two steps of forming and calibrating as they include many parallel automatic processes that rely on workers to help each other when interruptions occur. Our study focuses on the presses. Each press has an integrated palletizer for automatically storing pressed parts. We do not focus on the thermal treatment as it is a separate step in the production process since it is not batched, as the pressing processed, but involves more flow. The treatment group was a factory in Germany that encompasses 41 presses operated by 38 employees across three shifts in total. The control group was a factory in Italy that produces very similar products, encompassing 32 presses and 33 employees in three shifts.

The actual choice of the treatment and control group depended on the knowledge about the similarity of processes from the field. Still, it was also analytically verified by testing what group satisfied the parallel trend assumption of the DiD analysis shortly before a possible treatment began (see Section 5). This assumption is essential for rigorously testing the hypotheses. In this analysis, we made sure that we considered only candidate treatment groups that share comparable process types. This procedure is not perfectly random but uses stratification. Thus, we follow the tradition of quasi-experimental designs (Grant & Wall, 2009). Such designs have several strengths, like enhancing collaboration among academics and practitioners and making experiments more relevant (Grant & Wall, 2009). Especially in field experiments, carefully weighing the trade-offs in experimental design is important (Eckerd et al., 2020).

Prior to the experiment and to understand the current identification and helping behavior on the factory floor, we conducted a pre-study using a survey that also covers some demographic information, which the smartwatch data does not provide. We surveyed all workers who agreed to participate in the Italian factory location, including pressing but also adjacent processes like drilling, for example, to reach adequate power for correlational analyses. We obtained $N = 98$ responses, of which 87 were men. The average respondent has been employed by the company for 10.2 years (SD = 8.7). Respondents grouped themselves into the age categories of <20 (4.2%), 21–30 (34.4%), 31–40 (24%), 41–50 (12.5%), 51–60 (22.9%) and >60 (2.1%). The main learning from the pre-study was that identification with skills ("My skills that I work with define who I am") correlated significantly with self-rated helping behavior ($r = .24$, $p < .01$), indicating that identification may indeed be a possible leverage point to improve helping behavior. Importantly, we found that identification with skills ($r = .3$, $p < .01$) positively correlates with worker satisfaction, indicating that our treatment was initially more likely to increase satisfaction than decrease it.

4.5 | Variables and measures

The measures collected during the study are based on data gathered from the smartwatch-based system and employee surveys. The smartwatch-based system delivers objective measures of *helping behavior* and *productivity*, as recommended for operations management experiments (Bachrach & Bendoly, 2011). In addition, we measure several self-report variables using scale instruments like *identification with skills* (manipulation check), variations of helping such as *self-reported helping behavior* and *intention to help*, as well as the two covariates *identification with machines* and *emotional exhaustion*. Emotional exhaustion is not part of our theorizing, but we note the important role it plays in connection to identity. Other studies have shown that changing the pattern of identification at work can lead to stress but can also improve well-being by emphasizing a sense of competence and expertise through professional identity (Burke, 1991; Pratt et al., 2006).

We objectively measure *helping behavior* every hour by comparing two distributions for each individual worker: (i) the distribution of machine interruptions processed by this worker and (ii) the distribution of all interruptions that were visible on this particular worker's smartwatch. Take, for example, a worker and four machines (M1–M4) and assume that the worker can complete eight interruptions out of 16 visible on the smartwatch in total (effectiveness is constant). The worker can allocate their efforts differently, as illustrated in Figure 3.

On the left side of Figure 3, the worker worked regardless of location, personal preferences, and so forth, by distributing their work (i.e., number of interruptions) proportional to the problems on the factory floor. This behavior promotes the exchange of work on the factory floor. If all workers followed such a pattern, workers would perfectly share the interruptions and work as a team. Recall the earlier example of helping behavior where a machine was not running "clean." If a worker fills in for an absent coworker at a machine that they do not originally consider "theirs," the gray and white distributions become more similar. This (dis)similarity is the foundation of our helping behavior measure. The right side of the picture illustrates the negative team leader's example who evaluated long delays as ridiculous. It shows a clear preference of the worker and ignorance of tasks at M3 and M4. Such a division of work avoids exchange and puts the factory floor at risk of experiencing productivity losses, as the team leader regretted in the example. The complexity of the measure is necessary to account for the lack of clear-cut worker-machine assignments that laboratory work can simulate more easily. Digitalization has helped the firm overcome this legacy organization.

In summary, the more similar the gray and white distributions are in shape, the more the worker exchanged work with coworkers without formal recognition of the reward system (i.e., helping behavior) and regardless of what machine was interrupted. The more different the distributions are, the more the worker avoided exchange

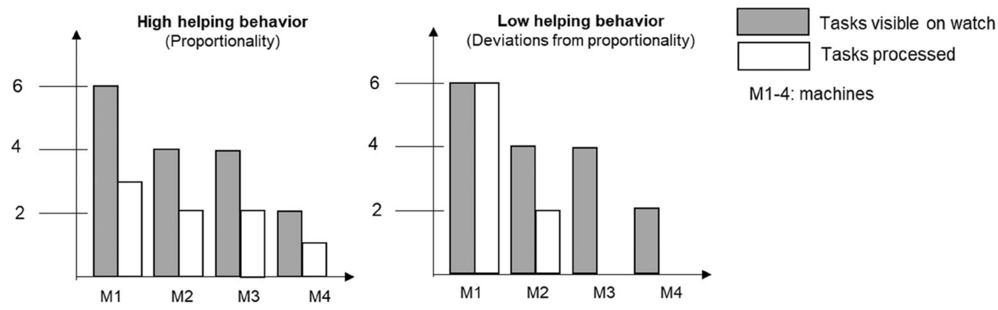

FIGURE 3 Illustration of helping behavior measure.

and focused on a narrow set of machines, although problems also occurred elsewhere. The equation below states this more formally. We measure helping behavior for a worker i by computing the coefficient of variation (CV; standard deviation/mean) among a set of M scores that each corresponds to a machine m. M is the total number of machines that were visible on the worker's watch. The M scores are quotients of the number of completed tasks and the number of visible tasks for each machine m. The CV of these scores is 0 when all machines m were addressed proportionally to all visible tasks and increases for deviations from proportionality. We divide the CV by the maximum value of the CV for the given number of machines M (i.e., $\sqrt{M-1}$) and reverse the number to arrive at an easily interpretable helping behavior measure. Thus, the final measure is 1 for the maximum possible helping behavior and 0 for no helping behavior at all.

$$\text{helping behavior}_i = \left(1 - \frac{\mathrm{CV}\left(\frac{\text{tasks completed}_m}{\text{tasks visible}_m}\right)}{\sqrt{M-1}}\right) \forall m \in \{1, \ldots, M\}$$

We measure our second observed variable, *productivity*, using the machines that record their unit output every hour and allow a comparison of achieved output with the expected output. We compute a quotient of the two output variables as our measure for productivity. The expected output is internal to the company and machine-specific performance benchmark derived from the technical specifications of a press, like its number of strokes per minute and planned downtimes such as setup. Both observed variables for *helping behavior* and *productivity* are captured automatically by the digital back-end system every hour.

We additionally assess two self-reported scales on *self-reported helping behavior* and *intention to help* to compare results based on the digital systems with those based on perceptions of the workforce in post hoc analyses (Van Dyne & LePine, 1998). Moreover, we measure workers' *identification with skills* using a shortened survey instrument based on Johnson et al. (2012) as a manipulation check. The surveys were administered using the smartwatch before and during the manipulation period to all workers of the treatment group once per shift to align them with our shift-level measurement period (see Section 4.7). We adopted established scales from the literature for all variables and shortened all constructs to single items to avoid survey fatigue, which is easily triggered among manufacturing workers. Single-item measures are appropriate when the concepts under study are sufficiently clear (e.g., unidimensional) or when field contexts do not allow detailed multi-item measurement (Wanous et al., 1997). Consequently, they have been used in high-quality operations management studies (Rea et al., 2021). All survey instruments are provided in Appendix C.

Factors known to affect helping behavior in the literature, like order stability and material handling ambiguity, follow a natural noisy pattern (close to random) and are held constant, respectively, in our study (Cantor & Jin, 2019). Furthermore, we controlled for the workload on the factory floor and its possible effects on helping behavior by computing a ratio between the number of clocked-in workers per hour and the number of running machines in that hour. We average these values in shift-level analyses. We furthermore registered actual changes in the skill matrix and change requests brought forward by workers that were rejected by team leaders (none occurred). Both can affect the potential for helping behavior via workers' identification with their skills. We also control workers' emotional exhaustion with a survey item and take the number of possible work accidents into account (none occurred).

4.6 | Bias treatment

We did not disclose the hypotheses of the study to workers, and the treatment neither allowed conclusions about the dependent variables of interest nor expected results, such that demand effects were reduced (Eckerd et al., 2020). Furthermore, information leakages from company staff to workers were unlikely as only few central project partners knew the underlying goal of the treatment. We informed them of the biases that demand effects can impose. Also, we did not expect demand effects to bias in the surveys due to power distance since we are not part of the firm's internal hierarchy. Research has shown that only strong and actively emphasized cues for desirable results will create measurable demand effects in experiments, whereas weak signals have no effect (De Quidt et al., 2018). Moreover, we did not expect workers to significantly alter their behavior due to our sheer presence (Hawthorne effect; Adair, 1984) since, first, employees have met us during several visits before and are used to interactions with the core research team and, second, we did not need to interact with the workers very often. We collected several variables from objective operational systems and only needed to visit the factory floor to encourage reflection of individual skill profiles and to ensure an appropriate response rate to the surveys. Workers received no compensation from us or the company that could induce demand effects.

4.7 | Estimation approach

The following DiD regression model results from our choice of variables and measures to test direct effects in our study. The example equation is designed to estimate the effect of the treatment on helping behavior among the groups g (treatment and control) at time t (shift-level data).

$$
\begin{aligned}
Y_{gt}(Productivity) = \beta 0 + \beta 1 \times [\text{Post}]_t + \beta 2 \\
\times [Treated\ group]_g + \beta 3 \\
\times [Post \times Treated\ group]_{gt} + \beta c + \varepsilon
\end{aligned}
$$

In the equation above, *Post* is a dummy that identifies the treatment period of the pre-post design and *Treated group* is a dummy that identifies the treatment group. The interaction effect $\beta 3$ is the most important coefficient for testing our hypotheses in a DiD regression model. βc is a vector of coefficients for control variables. It includes the workload and worker emotional exhaustion. We additionally control for workers' identification with machines in before-after-comparisons of the treatment group since the survey data is only available for that group. Two further pre-registered covariates were not included because no accidents occurred on the factory floor during the experiment and since the workforce did not file requests to have their skill profiles changed. We adapt this equation structure to investigate other direct effects like the effect of helping behavior on productivity and the effect of the treatment on helping behavior (see Figure 2).

The statistical power was sufficient during our study since we recorded a correlation between identification with skills and self-rated helping behavior of $r = .24$. This finding serves to approximate the correlation with actual helping and, accordingly, a sample size of 40 would be necessary to detect with 95% achieved power (repeated measures ANOVA, $r = .24$, α-level 5%, power 95%, 2 groups, 4 measures, 0.5 default r among measures). Because the outcome variable *productivity* is measured on the team level, the unit of analysis of our study is the team. We gather hourly data on helping behavior on the individual level and observe the productivity of the team's machines (unit output). Measuring the productivity of an individual worker is infeasible. We then aggregated individual scores of helping behavior to the group level by simple averaging.

With our treatment length of 2 weeks and a symmetrically long pretreatment phase, we obtained 3824 hourly observations in total that ensure sufficient power. We aggregated hourly measures to the shift level for the main analysis to match the shift-level perceptual scale measures. This means computing a mean of 8 h for each shift (early, late, and night). The attrition rate in the experiment was low with only one worker who chose not to answer the voluntary surveys. Our design is robust to this low level of attrition since we rely on group averages of our self-response variables, and the number of hours the experiment runs or data captured by objective variables are unaffected by attrition.

5 | RESULTS

5.1 | Analysis of survey responses

We first examined the survey data to ensure that our treatment was effective. We picked the surveyed variable for identification with skills ("My skills are very important to my sense of who I am at work.") and tested the difference of its distributions before ($n = 93$, 1 week pre-survey) and after ($n = 154$, two skill weeks) the start of the treatment after the Shapiro–Wilk test had indicated non-normal distributions. The nonparametric Wilcox rank-sum test indicated that the means before (4.83) and after (5.19) were significantly different at $p = .036$. We also examined the variables for emotional exhaustion and identification with machines and found that emotional exhaustion had declined from 4.97 to 4.37 (Wilcox test $p < .01$) and identification with machines had increased from 4.69 to 5.05 (Wilcox test $p = .046$). Thus, we conclude that our treatment of identification with skills was effective, that our intuition of reducing emotional exhaustion rather than increasing it was correct, and that identification with machines and skills seems to be related. We will discuss this further after the presentation of the main findings.

5.2 | Robustness checks

Before running our main estimations, we verified that we had a suitable control group. We had pre-selected comparison groups based on comparable size, processes, automation level, and so forth, and analytically tested the parallel trends assumption to find a suitable control group. The test examines whether the trajectories in terms of productivity of the treatment group and control group are similar before the treatment. This increases the certainty that differences measured after the treatment can be causally attributed to the treatment. In this analysis, it is essential that the interaction of a dummy that identifies the groups (*Treated group*) and a variable that increments between consecutive shifts is not significantly different from zero. If it were, it would indicate that the trends are not parallel but diverge. The DiD regression analysis for our treatment group in Germany and a comparison group in Italy resulted in a coefficient of $-.001$ ($p = .761$) for said interaction term, indicating that the trends did not change over time before the treatment phase. The low coefficient shows that the trends were near-perfectly parallel, making the Italian factory a suitable control group in our study. The left half of Figure 4 illustrates the trends.

5.3 | Main results

Having established the comparability of the German and Italian machine areas, we examined whether the treatment had increased productivity using the objective productivity data gathered from the manufacturing systems. We apply the DiD technique to investigate whether the difference in productivity among the treatment and control groups has changed because of the treatment. We find that the DiD, that is the interaction between *Treated group* and *Post*, is not significantly different from 0 ($B = -.009$, $p = .795$). The treatment did not influence productivity, leading us to reject Hypothesis 1. Table 1 summarizes the regression model, and Figure 4 shows the results graphically. The figure shows that both factories show parallel trends before and after the treatment, with no significant difference that could be attributed to the treatment. The full regression model details can be found in Table D1.

We examined whether identification with skills increased helping behavior with a similar DiD analysis. We find that the treatment had no significant effect on the objective helping behavior measure ($B = .017$, $p = .677$). Table 2 summarizes the regression model, and the full details are reported in Table D2. Self-reported helping scores from surveys are consistent with this finding: self-reported helping behavior ($B = -.024$, $p = .949$) and the intention to help ($B = -.071$, $p = .795$) do not differ before and after the start of the treatment. This result suggests rejecting Hypothesis 2.

Since testing the link between helping behavior and productivity (Hypothesis 3) is purely correlational in any case (i.e., we did not directly treat helping behavior), we run a simpler regression model than DiD that includes all control variables, including also the self-reported ones. We find no significant relationship between helping behavior and productivity ($B = -.090$, $p = .311$), which suggests rejecting Hypothesis 3. The full regression model is provided in Table D3.

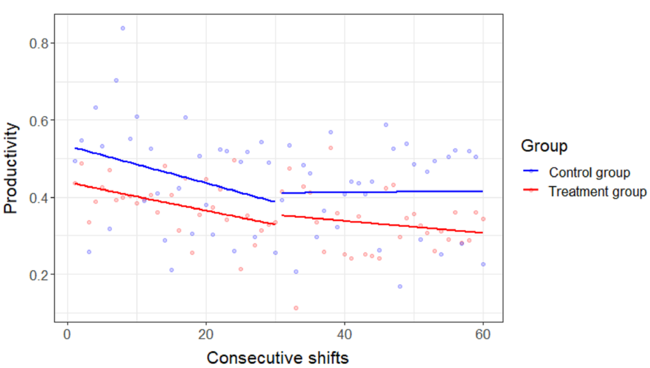

FIGURE 4 Linear trends of productivity before and after the treatment start.

6 | EXPLORING THE NULL RESULTS

We have proposed a research design that was rigorously reviewed before the data collection to rule out any

TABLE 1 Results of regression predicting productivity.

Dependent variable: Productivity	
Constant	0.433**
Treated group (group fixed effect)	Included
Post (time fixed effect)	Included
Treated group × *Post* (Hypothesis 1)	-0.009 ($p = .795$)
Control variates	Included
Adjusted R^2	0.349
Observations (shifts)	120

Note: **Significant at the .99% confidence level; Regression uses robust standard errors.

TABLE 2 Results of regression predicting helping behavior.

Dependent variable: Helping behavior	
Constant	0.424*
Treated group (group fixed effect)	Included
Post (time fixed effect)	Included
Treated group × *Post* (Hypothesis 2)	0.017 (p = .677)
Control variates	Included
Adjusted R^2	0.228
Observations (shifts)	120

Note: **Significant at the .99% confidence level; *Significant at the .95% confidence level; Regression uses robust standard errors.

mistakes in our identification strategy. For example, we significantly reduced concerns around the two most common sources for type II errors, poor measures, and lack of power (Landis et al., 2014). Further, we have pre-tested our assumptions by conducting a pre-study that provided preliminary data confirming the proposed effects. Therefore, we have significantly reduced the risks of errors due to methodological problems, supported by the review team and editors. Despite these joint efforts, we have obtained null results in our study beyond the significant manipulation check. Nevertheless, our nonsignificant hypothesis tests deliver valuable insights that can advance operations management literature and theory, as we discuss in the following. Generally, the interest in publishing null results is increasing (Mervis, 2014; Miller & Bamberger, 2016), and this special issue review process has significantly decreased possible publication biases. As the interest in field experiments of operations management scholars is increasing (Eckerd et al., 2020; Gao et al., 2023), innovative pre-registration publication processes are one way to ensure that studies using field experiments will not choose increasingly incremental and low-risk research questions to avoid the publication bias. Of course, null results are of significant managerial importance as they point to avenues for managerial intervention that are potentially less productive or point to the need to carefully adapt treatments before applying them again in the field or laboratory.

6.1 | Treatment strength

The field experiment design gives us the unique opportunity to go back to the company and discuss the findings with workers and the leadership of the company. A meeting including the chief digital officer, global head of business systems, several plant managers, and other senior managers illuminated ideas that may explain the results that seem disappointing at first sight. Why does the treatment not influence our dependent variables according to our DiD model? The first and most intuitive reason is the small treatment effect. We see a clear improvement in identification with skills in survey responses (+7.5%, p = .036), but this may have been too weak to affect the processes on the factory floor. The literature supported our approach to increase identification, as it suggests that changing one's identification is not as hard as one may think: "situated identification" can be triggered by situational cues in experiments, for example (Ashforth et al., 2008, p. 331). Still, we concluded together with the managers that it may be necessary to implement a higher emphasis on skills in continuous routines such as shift handover meetings to make a stronger impact and to see a clearer effect eventually.

As in most experimental studies, the effect sizes we measure depend on the manipulation strength chosen by the researcher and, therefore, should be interpreted and compared with caution (Cooper & Richardson, 1986). Thus, our results call for future studies on translating situated identification into deep identification in manufacturing settings. This also leads to another important limitation: we intensively surveyed the workers twice per shift and could not continue this data collection over a longer time to examine whether and how fast identification with skills returns to pretreatment levels. Our result also emphasizes the relevance of testing hypotheses using experimental designs in addition to relying on cross-sectional designs. Our initial power analysis showed a significant correlation between scores of identification with skills and self-rated helping behavior, which we failed to replicate in the experiment. This contrast shows again that pair-wise correlations from surveys like our pretest can be misleading and that experimental designs like our main study, including careful controls, consequential choices, and objective measures, are the preferred approach to pinpoint causality in many operations contexts (Bachrach & Bendoly, 2011). Experimental studies in other contexts where emotions or perceptions are central concepts may be set up differently after making important design choices (Eckerd et al., 2020).

6.2 | Connection of sub-identities

A second and more interesting explanation of our null results may lie in the survey results. In addition to identification with skills, we also observe that identification with machines has increased (+7.7%, p = 0.046). We paid careful attention to put the sole focus of the skills weeks on skills instead of other features like machines, but the treatment has still spilled over, so it seems. Our initial design was based on the literature that suggests that "identity is multidimensional, consisting of many different yet interconnected sub-identities. Although individuals typically hold several sub-identities, *only one* is believed to be active at any given point of time" (Miscenko & Day, 2016, p. 218). Our goal to address only one sub-identity was in line with this idea. For factory workers using digital task allocation systems, however, it appears, based on our results that skills and machines are of so tightly connected sub-identities that they can be hardly separated and are indeed active simultaneously. Figure B1 illustrates this: the skills are only defined with the appropriate machine type in our setting. A generic skill hardly exists since most skills are tied to a specific machine type, as in most other factories in industry too. The leading project manager for digitalized manufacturing in the German plant reflected on the two sub-identities as follows:

> We have increased the skill mindset, which has all the potential positive effects in terms of productivity, but it seems that skills and machines are connected more than we thought. We also increased the machine mindset, which has led to a canceling-out effect. Skill mindset drives teamwork, but machine mindset counteracts and invites workers to stay put at "their" machines again.

This points to a likely reason why we did not capture clear effects on helping behavior and productivity and opens new questions of how to separate sub-identities in production and whether that is possible at all. The project manager suspected that we had measured an aggregate effect of both types of identification on helping behavior and productivity. As one is likely positive, the other likely negative, and both can be assumed to have similar magnitudes due to similar increases in identification in the survey; they may cancel each other out to be null. This anecdotal result suggests a significant extension of the theoretical idea that only one sub-identity is active at the same time by showing that it is likely that two sub-identities were impossible to separate in our study and contributed to our null results.

6.3 | Reflections for future field experiment designs

In addition to theoretically expanding the idea of identification at work, our study can also practically guide future intervention studies or field experiments aiming to increase identification with skills. The notification element of our treatment (Figure B1) emphasized the top 5 skills, which were the most frequently used. These messages were customized for all workers. We argue that these reminders nudged workers to integrate all skills into their self-concept more, including those skills that are less used. Of course, the emphasis on the skills that are already frequently applied are the least powerful nudge for increasing helping behavior since it may reinforce workers' focus on this core skill set. This facet of our treatment design thus made it harder to find our proposed effect. We opted for this very conservative treatment design in our work to avoid revealing the goal to broaden workers' action radius, which is the basis for measuring helping behavior in this study. This approach may have been overly concerned with causing demand effects. We recommend future studies to emphasize the skills that have not been used by workers. This may trigger more intensive reflection and evaluation along the lines of "I had already forgotten that I can do this" or "I should go and apply this skill of mine again more often." The latter would have been a strong nudge toward teamwork, which we believe future studies can rely on without invoking any serious demand effects. With this slightly adapted approach, future work may be able to measure a stronger link between identification with skills and helping behavior on the factory floor.

6.4 | Effect on social sustainability

An unforeseen but welcome outcome of our intervention was a notable reduction in emotional exhaustion among the participants. While the primary goal of our intervention was to enhance performance, we observed that the well-being of workers is intricately linked to this aim. Emotional exhaustion is regarded as the main component of burnout syndrome (Maslach et al., 2001). It describes the basic stress component of burnout and refers to feelings of being overextended and depleted of one's emotional and physical resources. Explanations for the decrease in emotional exhaustion in our field experiment can be found in the literature about professional identity. Professional identity can be defined as the view of oneself as a professional, encompassing a sense of competence and expertise within a specific occupation or field (Pratt et al., 2006). It gives workers a sense of belonging and a secure base, enabling them to understand their work better and fostering a collective spirit within their professional community. It goes beyond mere role definition and encompasses a broader scope of possibilities for the individual professional, shaping their values, attitudes, and approach to their professional role. Moreover, developing a distinct role definition is pivotal for establishing one's professional identity within a specific field.

While emotional exhaustion is only a control variable in our work, the interplay between identity at work and burnout has been a subject of interest in various studies. A significant correlation between professional identity and burnout has been documented across diverse industries (Chen et al., 2020; Sabanciogullari & Dogan, 2015; Zhang et al., 2021). Our intervention specifically targeted an element of professional identity—the enhancement of workers' identification with their skills. By focusing on this aspect, we aimed to bolster the professional self-concept, thereby strengthening the individual's perception of themselves as integral members of their profession. This enhanced self-concept could potentially make work tasks feel less burdensome, as they are seen as intrinsic to one's identity rather than external obligations. Consequently, this shift in perception may lead to a decreased risk of burnout (Zhang et al., 2021). These findings imply that our intervention likely augmented the professional identity, serving as a buffer against burnout. This has substantial implications for the well-being of workers and their intentions to remain with the organization (Campbell et al., 2013). Future studies must further investigate these effects in more detail.

6.5 | Summary and limitations

We have discussed that (i) our manipulation may not have been strong enough to show an effect in a real factory; (ii) that two mechanisms based on two different sub-identities may be canceling each other out; (iii) that our treatment design may have been overly conservative and therefore was limited in its strength; (iv) and that our treatment has shown an unforeseen but welcome reduction in emotional exhaustion. These insights deliver new contributions to the discussion on identification at work, the research on burnout, and for future treatment design in the context of identification with skills. We also contribute to the behavioral operations literature on worker collaboration. We complement the prior work that has focused on the configuration of incentives (De Vries et al., 2016; Siemsen et al., 2007) and extend the discussion around what factors of intrinsic motivation can drive performance in operational teams (Franke et al., 2022). Specifically, we suggest that when teams are not implicitly forced to cooperate via task interdependence (Bachrach et al., 2006; Schoenherr et al., 2017), it is important to disentangle the competing effects of identification with skills and machines.

Beyond these values of our study, it is worth noting that it faces several inherent limitations that inform future research that may support our theory in other contexts. First, we are examining identification in a specific digitalized production system that involves operators that solve randomly occurring machine interruptions. Whenever work tasks do not appear randomly but according to a predetermined sequence, we cannot transfer our null results to those settings. This holds particularly true for other technology-enabled production organizations, especially those that follow a different process type compared to the batched mass production in our case. Digitalized assembly lines or job shops may deliver different conclusions. Assembly lines, for example, are characterized by high interdependency between process steps, which is not the case in our study. In our experiment, machine interruptions occur independently from each other. Moreover, job shops may include a much broader range of activities and different machines that can drive cognitive switching costs when workers move from one task to another. Finally, the cooperating company is a traditional manufacturer, and the workforce has an average tenure of about 10 years. Our results may not compare to organizations without a long tradition or ad-hoc production where workers have built fewer long-standing relations with each other.

6.6 | Managerial contribution

This study highlights a little-known mechanism on the factory floor: identification. We argued initially that identification with skills could be a non-tangible and low-cost leverage point to improve helping behavior—but we could not prove its effect in a field experiment in the manufacturing industry. Our study contributes to illuminating workers' identification change as an important managerial challenge. We were able to increase workers' identification with their own skills by about 7% over the course of 2 weeks, applying an intensive program of meetings, notifications via wearables, and visible posters and roll-ups. Reaping the rewards of higher identification with skills in the work context has proven to be a truly challenging endeavor since we could not show that the higher identification also translated into more cooperation among the workforce or overall productivity. However, we could observe a reduction in workers' emotional exhaustion. Our discussion, considering our theory and based on managerial insights, suggests that emphasizing skills on factory floors may also automatically emphasize the relevance of the machines and equipment. Skills and machines are inherently connected in our study. This leads to a possible cancelation effect: identification with skills may enhance helping, but this effect remains concealed since workers' increasing identification with specific machines makes them simultaneously avoid helping at machines that are not "theirs." This dual process requires further exploration in studies on identification in manufacturing.

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ETHICS STATEMENT

This research design has been accepted after review by the Ethics Commission for research with human participants at ETH Zurich.

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APPENDIX A

Script for the Meetings of the Skills Weeks

(to be distributed among researchers and team leaders beforehand)

Script for 4 Mini-Meetings on Skills, each lasting 10–15 min

(Responsible: researchers and managers; blinded)

Objective	Participants	Approach
• Promote identification of employees with their skills	• Employees of one shift	• Interactive
	• One team leader	• Open communication
	• One or two researchers	• No performance measurement or evaluation as goal

Guideline for all of us: The meeting should solely focus on individual skills, not on other aspects such as skill distribution within the team, team collaboration, compensation, the smartwatch system, technical issues, and so on.

Meeting 1:

- Employees receive an empty skill matrix and fill in their skills for solving interruptions.
- Then, each person receives their matrix as it is stored in the system.
- Objective: Comparison of self-assessment and system assessment.
- If desired, the employee can discuss the results with the team leader and request changes (control variable).

Meeting 2:

- HR provides information about current or upcoming skill development trainings.
- HR informs about current or future needs of (COMPANY) pertaining to skills.
- Development opportunities for employees' skills at (COMPANY).
- Illustrate ways and requirements to acquire set-up skills, for example.

Meeting 3:

- Employees receive their individual skill matrix as it is stored in the system.
- Which skills do I want to learn in addition or expand upon?
- Which skills can I learn particularly quickly based on my existing skills? Which ones are more challenging?
- How does this align with (COMPANY)'s offerings and plans (referring to Meeting 2)?

Meeting 4:

- Employees receive their individual skill matrix as it is stored in the system.
- Which skills outside of the skills matrix do you want to learn or expand?
- Which skills are important for production that are not represented in the system?

After the Skills Weeks:

- Mutual feedback. What went well? What needs improvement?

APPENDIX B

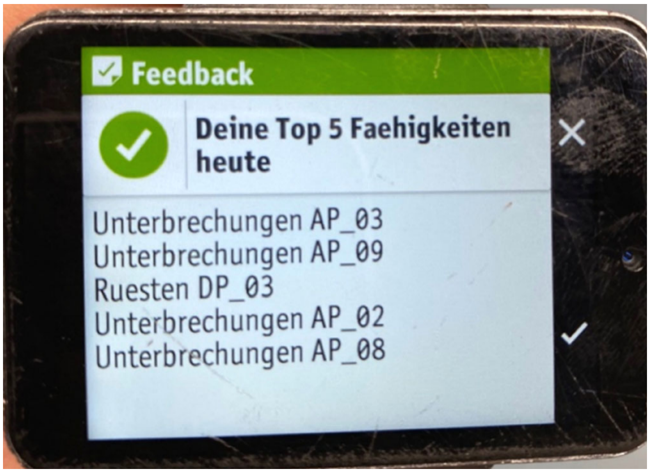

FIGURE B1 Skill message delivered via the smartwatch. The message shows codes for those skills that are the top 5 most frequently used skills of a worker. These codes are commonly known among management and the workforce. Messages like these were delivered at the beginning of each shift, reporting on the previous shift of that particular worker. A similar message was delivered at halftime of a shift, reporting on the current day for a particular worker.

APPENDIX C

C.1 | SCALE INSTRUMENTS

This appendix shows the single-item measures that were gathered via the smartwatch during every shift in the treatment group and the full measure structure. Short measures such as single-item measures are appropriate when constructs are unambiguous and have been used in operations management (Rea et al., 2021; Wanous et al., 1997). We show the dropped items (white background) along with the single items we used in the study (gray background).

Identification with Skills (subscale of Johnson et al., 2012) (Not at all 1—Very much 5)

- My self-identity is based on the skills I use at work. (dropped)
- My skills are very important to my sense of who I am at work.
- My sense of self overlaps with the skills I required for my work. (dropped)
- If someone criticized my skills that would influence how I thought about myself. (dropped)
- I identify strongly with my skills at work. (dropped)

Helping Behavior (short scale, Van Dyne & LePine, 1998) (Not at all 1—Very much 5)

- I help others in this group with their work responsibilities.
- I get involved to benefit this work team. (dropped)
- I volunteer to do things for this team. (dropped)
- I assist others in this group with their work for the benefit of this team. (dropped)

Intention to Help (based on Ajzen, 1985) (Very unlikely 1—very likely 7)

- How likely is it that you will help a colleague in the next shift?

Identification with Machines (subscale of Johnson et al., 2012) (Not at all 1—Very much 5)

- My self-identity is based in part on the machines I commonly use at work. (dropped)
- The machines I commonly use are very important to my sense of who I am at work.
- My sense of self overlaps with the machines I commonly use for my work. (dropped)

- If someone criticized the machines I commonly use at work that would influence how I thought about myself. (dropped)
- I identify strongly with the machines that I commonly use at work. (dropped)

Emotional Exhaustion (subscale of Kristensen et al., 2005) (Never 1—Always 5)
How often are the following statements true? (dropped)

- Do you feel burnt out because of your work?
- Does your work frustrate you? (dropped)
- Do you have enough time for family and friends during leisure time? (dropped).

APPENDIX D

TABLE D1 Main analysis for Hypothesis 1: DiD regression predicting productivity.

	Estimate	Standard error	*t* Value	*p*-Value	CI lower bound	CI upper bound
Intercept	0.433	0.128	3.393	.001	0.180	0.686
Treated group (group fixed effect)	−0.058	0.055	−1.050	.296	−0.168	0.052
Post (time fixed effect)	−0.049	0.028	−1.749	.083	−0.104	0.006
Late shift	0.025	0.020	1.253	.213	−0.015	0.065
Night shift	−0.103	0.021	−4.84	.000	−0.145	−0.061
Workload	0.230	0.580	0.397	.692	−0.918	1.378
Treated group × Post	−0.009	0.036	−0.261	.795	−0.081	0.062

Note: Regression uses robust standard errors; Including the survey-based control variables was not possible in the DiD regressions since the control group could not be surveyed in the field; R^2-adjusted: 0.349.

TABLE D2 Main analysis for Hypothesis 2: DiD regression predicting helping behavior.

	Estimate	Standard error	*t* Value	*p*-Value	CI lower bound	CI upper bound
(Intercept)	0.424	0.168	2.522	.013	0.091	0.757
Treated group (group fixed effect)	−0.098	0.068	−1.454	.149	−0.232	0.036
Post (time fixed effect)	0.046	0.036	1.301	.196	−0.024	0.117
Late shift	0.015	0.025	0.600	.549	−0.034	0.064
Night shift	−0.023	0.024	−0.963	.338	−0.070	0.024
Workload	0.245	0.726	0.338	.736	−1.192	1.683
Treated group × Post	0.017	0.04	0.417	.677	−0.063	0.097

Note: Regression uses robust standard errors; Including the survey-based control variables was not possible in the DiD regressions since they are only available for the treatment group; R^2-adjusted: 0.228.

TABLE D3 Main analysis for Hypothesis 3: Regression predicting productivity.

	Estimate	Standard error	*t* Value	*p*-Value	CI lower bound	CI upper bound
Intercept	0.490	0.202	2.424	.019	0.084	0.896
Helping behavior	−0.090	0.088	−1.022	.311	−0.265	0.086
Post (time fixed effect)	−0.028	0.031	−0.924	.360	−0.090	0.033
Late shift	0.040	0.023	1.736	.088	−0.006	0.087
Night shift	−0.010	0.023	−0.422	.674	−0.057	0.037
Workload	−0.844	0.722	−1.169	.248	−2.292	0.605
Emotional exhaustion	−0.018	0.020	−0.900	.372	−0.059	0.022
Identification with machines	0.023	0.029	0.786	.435	−0.035	0.081

Note: Regression uses robust standard errors; Group fixed effects cannot be modeled in this regression because the bottom two control variables are only available for the treatment group; R^2-adjusted: 0.162.