FACULTY OF PSYCHOLOGY
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The development of nudge interventions to promote safety behaviour in an industrial production environment

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CHAPTER 1

INTRODUCTION

In modern industrial landscapes, safety is an increasingly important cornerstone guarding against the hazards that lurk within the operations of the heavy process industries (Knegtering & Pasman, 2009) such as the steel industry (Nazaripour et al., 2018). The concept of industrial safety, which has a rich historical backdrop (Swuste et al., 2010), finds itself both perpetually relevant and continually evolving in response to the dynamic demands of our contemporary world (Hofmann et al., 2017). In this doctoral thesis, we embark on a journey that explores industrial safety's historical roots, confronts the contemporary impasse in safety innovation and seeks to elaborate on a transformative path forward through the lens of behavioral science. More specifically, we do this by assessing the relevance of emerging dual process theories of decision-making (Evans & Stanovich, 2013) and the practice of nudging (Thaler & Sunstein, 2008).

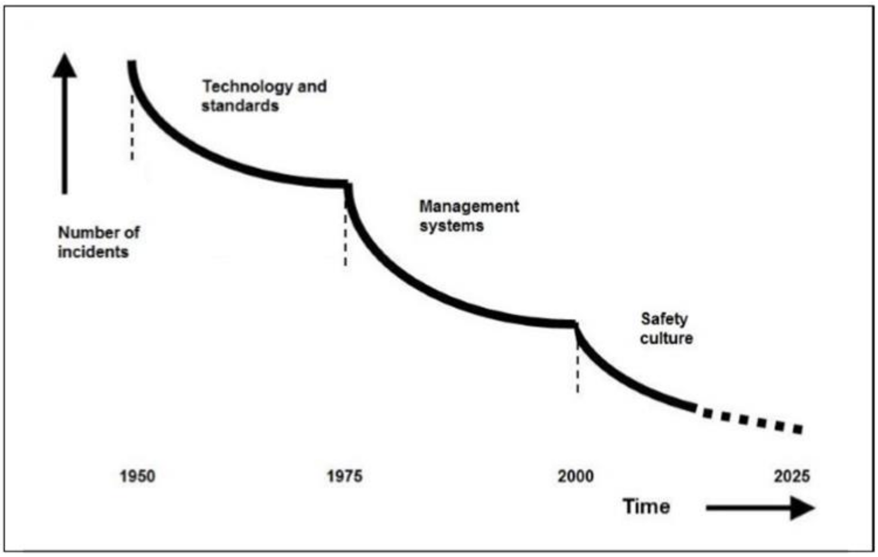
INDUSTRIAL SAFETY: A HISTORICAL PERSPECTIVE AND MODERN CHALLENGES

The history of industrial safety is a compelling narrative that traces its origins to the Industrial Revolution of the 18th century, a period marked by rapid industrialization and the emergence of new hazards (Barham, 2013). Factories and manufacturing plants became places of progress, but also of peril and severe accidents, increasing the concern for worker safety (Palmer, 1926). Occupational safety is vital for societies, as it safeguards worker well-being and minimizes societal costs associated with workplace accidents. For businesses, it bolsters their reputation, attracts stakeholders, ensures their 'license to operate' that is monitored by governments and contributes to long-term success by ensuring a healthy and productive workforce. This makes a safe workplace a 'sine qua non' for successful industrial organizations (Fernández-Muñiz et al., 2009; Haslam et al., 2016).

In the last decades, industrial safety has seen a remarkable decrease in incident rates through improved technology, standards, regulation, management systems and, more recently, safety culture approaches (Figure 1) (Hudson, 2007). However, further improvements in the last years seem to have stagnated and to have reached a plateau (Lindhout & Reniers, 2017). Research has shown that up to 90% of occupational accidents are related to human errors (Kletz, 2001). Therefore, experts indicate that a better understanding of safety behavior and behavior change is one of the last main issues to resolve (Spigener et al., 2022).

Figure 1

The number of industrial incidents in the last decades (after Hudson, 2007)



Human Error, Safety Culture and Behavior-Based Safety

More than improved machinery and protocols, it is essentially changing human behavior and environmental factors that significantly determine safety outcomes (Geller, 2005). Therefore, understanding the intricacies of how individuals make decisions in safety-critical situations is paramount. The work of Reason (1990, 2000) has mainly been devoted to investigating the role of human error, pointing out the difference between human factors that are unintentional (e.g., attention deficits and memory lapses) and more intentional ones (e.g., deliberate violation of the rules), and the relevant difference between a person approach and a system approach of safety. While a person approach tends to treat human error and unsafe behaviors as moral and motivational issues ('bad things happen to bad people', see also Lerner et al. (1970)), he claims that the preferred system approach concentrates on conditions under which individuals work and aims to avert error by building multiple lines of defense (e.g., enhanced procedures, improved supervision and better working conditions) (Perneger, 2005).

Following the growing attention for safety behavior and conditional factors, in the 1980's and 90's the concepts of 'behavior based-safety' and 'safety culture' were developed and they gained more popularity since the year 2000 (Hudson, 2007). They are, in addition to technological safety processes and safety management, the main subjects of research, addressing the human - and organizational - factors behind unsafe behavior (Spigener et al., 2022). However, these existing behavior based frameworks for safety do not consider all aspects of human behavior and are often based on implausible assumptions about (the deliberateness of) human behavior. Behavior-based safety is currently merely and essentially the application of applied behavior analysis and modification in a safety context (Geller, 2005). It is well known for the powerful principles of operant conditioning and the reinforcement theory that have proven to be successful in behavior change efforts in a variety of clinical and applied contexts (Kazdin, 1973; Nemeroff & Karoly, 1991). For example, positive reinforcement might increase the use of protective equipment at a construction site. However, when this reinforcement is no longer provided, the usage of this protective equipment is expected to gradually drop back to the baseline (Saari, 1992; Zohar et al., 1980). In relation to safety, the logic of the culture change approach is that the organization's basic assumptions and values widely influence the effort that is done and the initiatives that that organization takes to manage safety. These activities shape, in turn, the perceptions and expectations of the employees regarding the importance of safety, safe work practices, hazard control, incident reporting and so on (DeJoy, 2005).

While behavior-based safety and the current safety culture approach have both proven to be valuable and important ways to approach safety, both seem to focus largely on conscious and rational decision-making either through changing the values, perceptions and beliefs held by an organization (i.e., culture) or by using operant conditioning (e.g., reinforcement) in order to alter certain critical safety-related behaviors. These approaches do not take sufficiently into account that many actions are not a result of deliberate or conscious reasoning, but rather an automatic and often unconscious behavioral response elicited by a certain context or environment (Simon, 1955; Thaler et al., 2012). As a result, such behavior largely falls outside the reach of current safety behavior approaches that focus predominantly on deliberate action and remain a source of incidents (Lindhout & Reniers, 2017). Instead, in this doctoral thesis, we approach safety behavior from the premise that human behavior is not perfectly rational, deliberate, and consistent. In the following section, we first explain why human behavior is not entirely rational and consistent and how these insights can be leveraged to assist behavior change initiatives. After that, we clarify how leveraging these insights is vital to advance industrial safety management by addressing the challenges it currently faces.

BOUNDED RATIONALITY AND THE PRACTICE OF NUDGING

There is a difference between actions resulting from deliberate and conscious reasoning and actions that can be seen as a rather effortless, automatic and often unconscious response elicited by the environment. This is referred to by Noble Prize laureate Kahneman (2011) as 'system 1 and system 2 thinking', a widely accepted metaphor for dual-process theories of decision-making (Evans & Stanovich, 2013). System 1 thinking is a more automatic, fast and unconscious way of thinking that requires little effort and is associated with no feeling of control. This is seen as a more instinctive way of 'thinking' or decision-making and includes subconscious values, drives and beliefs that influence our 'gut reactions'. Examples are the tendency of people to link a green color to health (Tham et al., 2020), directing attention to a flashing light (D'Egidio et al., 2014), as well as automatically forming stereotypical mental associations about social groups (Payne & Hannay, 2021). System 2 thinking is considered a more rational way of thinking and is associated with the subjective experience of power to act, choice and concentration. It includes conscious attention for the mental effort that is being done. Examples are trying to remember something, comparing the price-quality of products and focusing attention in a noisy room. In short, the interaction between both systems can be understood in the following way. Both systems are almost always active, but while system 1 generates constant impressions, intentions, feelings and automatic reactions, system 2 only interferes when things become complex or do not go as planned (Kahneman, 2011).

The insight that system 1 plays a vital role in human behavior and that environmental (often irrelevant) factors easily influence it, gave rise to a series of psychological studies of how behavior can be influenced by modifying or implementing these specific factors. Those studies build on the premise of 'bounded rationality' (Simon, 1955), including that our behavior and decision-making are fundamentally biased, driven by system 1, and that the capacity of system 2 is limited (e.g., memory lapses) and needs further assistance. In their book 'Nudge', Thaler and Sunstein (2008) put forward the concept of 'nudging', meaning literally 'to give a little push', to address this practice. They suggest that people should be guided and supported in making the right decisions to promote the more preferred behavior by altering the choice architecture surrounding this behavior – i.e., the physical, social and psychological aspects of the context that influence our choices (Thaler et al., 2012). Thaler and Sunstein (2008) define a nudge as *"any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be cheap and easy to avoid. Nudges are not mandates. Putting fruit at eye level counts as a nudge. Banning junk food does* *not."* (Thaler & Sunstein 2008, p. 6). A popular example is the use of defaults to increase organ donation. By changing opt-in to opt-out formats (i.e., no action required), one can leverage people's tendency to inertia (i.e., people will only do the effort if they have strong preferences) and increase the number of organ donations up to 99% (Davidai et al., 2012). Other examples are the use of text reminders to increase vaccine uptake (Milkman et al., 2021) or placing healthy food at eye level to promote consumption (Bucher et al., 2016).

The way that Thaler and Sunstein (2008) define a nudge is very inclusive and until today, what is exactly meant by 'a nudge' is still a matter of debate (Berthet, 2022). More important it is to understand that the subconscious system 1 and the limitations of system 2 have a significant impact on how we make decisions and that this influence can often easily be altered by simple interventions in the direct choice environment.

Before delving into the relevance of nudging for industrial safety, we provide a brief overview of nudge effectiveness, ethical concerns and considerations for its strategic development.

Nudge Interventions: Effectiveness, Cost-Effectiveness and Ethical Considerations

Nudge interventions have been studied and implemented successfully in several domains, including health and well-being (Hanks et al., 2012; Johnson & Goldstein, 2003), saving and financial decision-making (Thaler & Benartzi, 2004), climate preservation and sustainability (Bergquist et al., 2023), education (Weijers et al., 2021) and so forth. In general, most of the nudge interventions seem to be effective, generating a small effect on average (DellaVigna & Linos, 2022), but recent debates highlight the need for careful investigation of the context and the design of the nudge to increase the probability of success (Bryan et al., 2021; Hallsworth, 2022; Sunstein, 2017). This highlights the need to investigate if known nudging techniques work in an industrial safety context as well, instead of copy-pasting and assuming they will. In addition, a big gap exists in current nudging literature concerning the long-term effects of the interventions, with mixed results to date (Allcott & Rogers, 2014; Congiu &

Moscati, 2022; Van Rookhuijzen et al., 2021). In this doctoral project, we were able to evaluate nudge effects over an extended period (up to 1.5 years, discussed in CHAPTER 4), making the findings even more valuable.

A recent study of Benartzi et al. (2017) examined the cost-effectiveness of nudges compared to more typical intervention strategies of the government (United States and United Kingdom), like financial incentives. They found that nudges often yield particularly high returns at a low cost when it comes to boosting retirement savings, college enrolment, energy conservation, and vaccination rates. Some nudge interventions reached ratios from 10:1 – 100:1 (i.e., 100-dollar return for every dollar invested), exceeding common return of investment ratios of informational campaigns (14.68) and economic tax incentives (1.24).

Frequent debates concerning the ethical aspect talk about whether it is legitimized to alter people's behavior in often covert ways without consent of the individuals whose behavior is being altered (Lin et al., 2017). In the case of safety, it is more obvious that nudging is always beneficial to the organization that executes the intervention, but also to the individual whose safety is targeted. In addition, one could argue that you cannot 'not influence' behavior, as choice architecture is always present. As such, it can be considered unethical not to change a context that elicits (or nudges) unsafe behaviors (Sunstein, 2015). In CHAPTER 7, the general discussion, we return in detail to the ethical dimensions to consider when developing and implementing nudge interventions.

Strategic Nudging: A Choice Architecture Taxonomy

To structure and inform nudge development, we use the taxonomy of Münscher et al. (2016) consistently throughout CHAPTERS 3, 4 and 5. This frameworks stands out as a highly comprehensive and systematic approach, and puts forward three distinct nudging (or choice architecture) clusters. Each cluster is built around a distinct psychological barrier and covers unique behavioral techniques (see Table 1 for a detailed overview).

The first cluster, known as 'Decision Information', concentrates nudges improving the accessibility, clarity, and personal relevance of decision-relevant information. For instance, *social norm messages* communicate peer values and the occurrence of actual behaviors (e.g., "75% of you colleagues do X") to influence decision-making (Bicchieri, 2017), and proved successful in, among others, promoting energy conservation (Allcott, 2011). *Framing* alters the presentation of information to sway choices, including framing of gain or loss (e.g., "new method with 5% chance to live" versus "95% to die") that have shown to influence doctors' decision-making (McGettigan et al., 1999). *Performance feedback*, on the other hand, provides individuals with insights into their own behavior that can elicit corrective action (House et al., 2022).

The second cluster, 'Decision Structure', covers techniques that take advantage of the context-dependent nature of decision-making by manipulating the arrangement or format of choice options, or by altering the required effort. D*efaults*, as previously discussed, make the desired outcome the standard setting (i.e., opting-out) and have shown to promote organ donations (Davidai et al., 2012). *Altering choice-related effort* has shown to influence the consumption of healthy food or tobacco by making it more or less convenient, respectively (Hollands et al., 2017). A third example includes *changing the order of choice options,* with recent studies showing that sustainable food options on top of the menu are chosen more (Langen et al., 2022).

The third and final cluster, 'Decision Assistance', is dedicated to bridging the gap between intention and action by strengthening self-regulation. Nudges in this cluster aim to reduce inadvertent behaviors stemming from restricted attention, memory lapses, and a lack of self-discipline. Strategies encompass the use of *reminders* that have been instrumental in boosting vaccination uptake via text-messages (Milkman et al., 2021) and, for instance, *salience* (or 'attention-drawing') nudges promoting safer behaviors by using bright-colored tread edge highlighters to prevent falling (Foster et al., 2014).

In sum, Münscher et al.'s (2016) taxonomy empowers researchers and practitioners to align their interventions strategically with specific objectives and the psychological barriers that individuals may encounter. This comprehensive framework offers a structured approach to implement nudging in industrial safety, facilitating more effective means to influence decisions and elicit behavior change.

Table 1

Choice architecture taxonomy of Münscher et al. (2016) (After Mertens et al., 2022)

Psychological barrier	Intervention category	Intervention technique
Limited access to decision-relevant information	Decision information: increase the availability, comprehensibility, and/or personal relevance of information	Translate information: adapt attributes to facilitate processing of already available information and/or shift decision maker's perspective Make information visible: provide access to relevant information Provide social reference point: provide social normative information to reduce situational ambiguity and behavioral uncertainty
Limited capacity to evaluate and compare choice options	Decision structure: alter the utility of choice options through their arrangement in the decision environment or the format of decision making	Change choice defaults: set no action default or prompt active choice to address behavioral inertia, loss aversion, and/or perceived endorsement Change option-related effort: adjust physical or financial effort to remove friction from desirable choice option Change range or composition of options: adapt categories or grouping of choice options to facilitate evaluation Change option consequences: adapt social consequences or microincentives to address present bias, bias in probability weighting, and/or loss aversion
Limited attention and self-control	Decision assistance: facilitate self-regulation	Provide reminders: increase the attentional salience of desirable behavior to overcome inattention due to information overload Facilitate commitment: encourage self or public commitment to counteract failures of self-control

NUDGING INDUSTRIAL SAFETY: A PROMISING APPROACH

The effective application of nudging in certain fields, such as pension saving (Thaler & Benartzi, 2004) and organ donations (Davidai et al., 2012), has served as a catalyst for researchers to explore its possibilities in other domains where human decision-making is key (e.g., environmental conservation and education, see Bergquist et al. (2023) and Weijers et al. (2021)). While numerous safety interventions, including signs, arrows, and color-coding, fit the definition of nudges, there is a gap in research exploring the potential of nudges as an established industrial safety strategy (Lindhout & Reniers, 2017). The limited studies that do exist are concentrated primarily on traffic safety (Avineri, 2014). An example from the traffic safety domain indicates that smiley faces can enhance the efficacy of speed feedback displayed on digital signs (Gehlert et al., 2012), driven by social (dis)approval and emotional influence (system 1). However, research on industrial safety nudges remains scarce, hindering a comprehensive understanding of their impact.

Industrial safety is likely to benefit from systematic nudge interventions, and the related behavioral insights, for two main reasons. The first reason includes the central role of behavior in safety performance, with up to 90% of the accidents being human error related (Kletz, 2001), and the discussed lack of innovative psychological frameworks to deeply understand subliminal behavioral drivers (i.e., beyond behavior-based safety and safety culture). The second relates to the physical and cognitive demanding nature of industrial production environments. In his work, Kahneman (2011) explains how an 'exhausted system 2' (e.g., due to fatigue, task complexity, time pressure or sensory overstimulation) tends to fall back on system 1 functioning. Meaning that in demanding situations, such as unforeseen production shutdowns with increased time pressures or extreme temperatures, people tend to be less susceptible for system 2 reasoning, which is dominantly targeted by current safety approaches (i.e., informational safety trainings and extensive safety protocols).

This idea of the exhausted system 2 is supported by the results of an exploratory mobile eye-tracking experiment we performed in preparation of the doctoral thesis. We recruited a convenience sample of 60 employees of the steel plant involved in this doctoral thesis (see following section), divided them in two groups of thirty persons (balanced for age, seniority and function), and tasked them with identifying as many hazards as possible (i.e., looking while wearing a mobile-eye tracker and say out loud what hazards they see) with differing time restrictions. One group got 1 minute to identify the hazards and the other 20 seconds, alternating over 4 situations (thus, each group has 2x1minute and 2x20 seconds trials). One of the main conclusions from the pilot study is that the 20 seconds time condition, compared to 1 minute, led to a relatively much less fixation time on hazards that required more reading or interpreting of multiple symbols for both groups (see Figure 2 and 3, green = less fixation, red = more). This aligns with the idea that safe actions requiring more cognitive effort (system 2) are more sensitive to taxing contextual factors such as time pressure, than other features that address system 1 more directly (e.g., use of colors, sounds, simplified signs and symbols). By strategically integrating nudges that target system 1 processing more directly, this renewed safety approach can address behavior change more holistically and effectively, especially in critical and demanding situations like (hazardous) unexpected crises with intense time constraints.

Figure 2

Heat map of the 1 minute group

Figure 3

Heat map of the 20 seconds group (with visibly less fixation at the flawed information sheet gas

In their work, Lindhout & Reniers (2017) highlight the potential of nudge interventions to promote safety in heavy process industries, but underline the need for pioneering field experiments. This doctoral thesis is such an pioneering endeavor and is the first to systematically investigate and empirically test whether nudges are effective in reducing unsafe behaviors in an industrial production environment. For this end, a series of large field experiments is carried out in the steel industry; as discussed in CHAPTERS 3, 4 and 5.

The Belgian Steel Plant Involved

The field experiments in this doctoral thesis are carried out at the Belgian sites of a multinational steel producer who is strongly familiar with the challenges that modern day industrial safety faces. Although the safety standards at this Belgian steel plant are high, a couple of thousands of incidents (i.e., potential accidents) still do occur at their sites on a yearly basis. These incidents sometimes result in severe or even fatal accidents (e.g., a fatal accident in 2021). Considerable numbers of the reported incidents are categorized with a 'severity level 5', which means that they could have led to a potential fatal accident. The number of level 5 incidents at this plant during the year 2019 (i.e., at the start of the project) in the following domains were the most prominent: Working with loads (140), LOTOTO procedure (i.e., making sure machines are free of energy before working on it or trespassing nearby) (129), Working at height (109), Traffic & Railways (78), Falling objects (122) and Gas hazards (39). These domains account for 85% of all the level 5 incidents, amounting on average to two severe incidents per day, and therefore constitute a central focus point throughout this doctoral thesis. It also aligns with research indicating that these domains account for up to 73% of all occupational accidents in the Netherlands (Lindhout & Reniers, 2017).

Their current safety approach focusses on the following aspects. There is a big focus on constant technological innovation such as safer machines, better Personal Protective Equipment (PPE) and improvements in safety protocols. They make sure that everybody receives the appropriate (safety) training to execute their function and provide additional trainings for specific target audiences such as the crisis teams. Prevention advisors walk around at the sites to check for safety-related problems and to monitor the compliance of the safety protocols and new employees get a mentor appointed to adapt easier to the current safety protocols. They launched an international health and safety initiative, with which they try to reduce the number of severe accidents to zero by setting up global standards and "Golden rules" of safety (see Figure A1 in Appendix 1A). Recently they started to focus increasingly more on the human factor behind the unsafe behavior and introduced a new safety training wherefore they select influential employees on the work floor to become stewards and to boost shared vigilance among the workers, aiming to create a new and better safety culture.

All these interventions bear witness of a great effort to reduce the number of incidents and the unsafe behavior at the sites, but they all have one thing in common; most of them focus largely on the system 2 of decision-making and deliberate behavior. This is not necessarily a bad thing as system 2 interventions (e.g., training, protocols, safety talks) and basic safe infrastructure and machinery are the basis of a good safety policy (Hofmann et al., 2017; Olson et al., 2016; Spigener et al., 2022); but this dominant focus on system 2 in the current safety interventions also shows that there is room for other additional interventions that address directly to system 1 and assist system 2 limitations. This new focus may be the key to surpass the safety plateau that many industrial companies, like the steel plant involved, have reached.

ADVANCING APPLIED BEHAVIORAL SCIENCE

In an era marked by transformative technological advancements and a growing understanding of human behavior (incl. bounded rationality), the field of applied behavioral science stands at the threshold of unprecedented possibilities (Hallsworth, 2023; Mills, 2022). These includes novel methods that advance the practice of nudging, but also new behavioral tools, informed by bounded rationality, that extent beyond nudging. In CHAPTER 6, we look ahead to some innovative ways of incorporating artificial intelligence (AI) to identify cognitive biases (i.e., a systematic distortion of judgement, Tversky and Kahneman (1974)), personalize (nudge) interventions for more impact and to grasp the complexities of underlying behavioral drivers, that are all relevant but not limited to industrial safety. We also focus on some related environmental, social, and economic costs associated with behavioral AI applications (Erion et al., 2022; Ryan, 2020). The aim is to clarify the dynamic interplay between AI, organizational decision-making and the multifaceted spectrum of behavioral techniques that poses both challenges and opportunities (Mills et al., 2023). In addition, in the general discussion (CHAPTER 6), we expand the scope beyond nudging by showing how other tools, such as 'behavioral audits' (Sunstein, 2022), can inform on and leverage human bounded rationality in future behavior change initiatives. Our structured outlook provides novel possibilities to steer safety behavior in the right direction and aims to enrich the current scope of applied behavioral science beyond mere choice architectural (or nudge) interventions (Ewert, 2020). These advancement equally enable changes in the larger systems in which fallible individuals operate (Chater & Loewenstein, 2022). CHAPTER 6 and the following general discussion (CHAPTER 7) do provide guidance in the rapid changing landscape of applied behavioral science by offering insights, frameworks, and critical reflections on the current state of the art and the path forward.

NUDGING SAFETY AMIDST THE COVID-19 PANDEMIC

As this doctoral thesis took shape, the world grappled with an unprecedented challenge—the COVID-19 pandemic. The pandemic disrupted lives, economies and research activities, including ours related to industrial safety in (impacted) workplace settings (Ingram et al., 2021). Social and behavioral science soon proved vital to support the pandemic control (Van Bavel et al., 2020). Therefore, in response to this unforeseen challenge, two field experiments were carried out, leveraging the principles of nudging to encourage adherence to COVID-19 guidelines. One of them, focused on promoting hand hygiene, is included in this doctoral thesis, because the insights gained on social influence are highly relevant to industrial safety (Casey et al., 2017). This study constitutes the first empirical chapter (CHAPTER 2), serving as a prelude to the broader application of nudging in the realm of safety.

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CHAPTER 2

NUDGE INTERVENTIONS PROMOTING HAND HYGIENE: A LARGE-SCALE FIELD EXPERIMENT IN AN INDUSTRIAL PLANT[1]

This study investigated the effectiveness of nudge interventions promoting hand hygiene in an industrial plant during the COVID-19 pandemic. A large field experiment was conducted with 861 participants and 14,645 observations. The interventions involved manipulating the placement of alcohol gel dispensers, the presence of social norm messages, and the placement of footstep stickers on the ground. All interventions significantly increased the usage of alcohol gel dispensers, with the combination of placement and social norm message providing the greatest results, increasing usage by 47%. People passing by in groups had a higher probability of using the dispenser than individuals, and this effect appeared to be solely mediated by the leading example of the first person in the group using the dispenser. The findings provide guidance for promoting health and safety compliance within organizations to combat surging infection rates related to COVID-19 and other infectious diseases, such as the seasonal flu.

Keywords: Nudging; Hand hygiene; Infectious diseases; Field experiment; Herd behavior; Social Norms; Process Industry

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INTRODUCTION

Hand hygiene is a critical factor to prevent illness and counter the spread of infectious diseases (Aiello et al., 2008; Wong et al., 2014). Good hand hygiene practices have shown to, among others, reduce illness-related absenteeism, at work (Arbogast et al., 2016) or schools (Wang et al., 2017), mitigate food poisoning (Lee et al., 2017) and prevent detrimental or even fatal hospital-acquired-infections (HAIs) (Boyce & Pittet, 2002; Jefferson et al., 2009). More recently, it also appeared as one of the important safety guidelines to prevent the spread of the coronavirus (SARS-CoV-2), in public and in the workplace, during the pandemic (Brauner et al., 2021; Ingram et al., 2021). To date, multiple vaccines have proven effective against this coronavirus reducing hospitalization, severe illness and excess mortality drastically (McDonald et al., 2021). Yet, the higher risk for fatalities in developing countries (Levin et al., 2022) and the potential increasing chance of future pandemics, due to climate change (Mora et al., 2022), indicate that insights into pandemic control, and combatting the spread of infectious diseases in general, remains of primordial importance. Next to vaccination, it became evident that human behavior plays an important role in controlling such a pandemic and infection. Good hand hygiene, social distancing, the wearing of mouth masks, ventilation and a significant reduction in social contacts, appeared to be the core aspects to battle the spread of the virus (Brauner et al., 2021; Ingram et al., 2021; Talic et al., 2021). Preventive behavioral measures to stop the spread of viral infections, like disinfecting hands, have been more common and promoted in health environments because health risks are greater in these contexts (Allegranzi & Pittet, 2009). However, the coronavirus and other viruses like the seasonal flu penetrate all levels of society, endangering also other vulnerable groups of people (Mirzadeh & Khedmat, 2022; Liu et al., 2021), including the workforce of organizations and their social networks. The present paper aims to assess whether behavioral interventions can be used to promote good hand hygiene in a non-health private company context and hence to evaluate if these behavioral interventions could assist in controlling the spread of these viruses.

Especially in environments with many social interactions, effective safety measures against the coronavirus are critical. Not only in the context of Corona, but also for other diseases that may compromise employee health and absence. Previous studies have shown that influenza accounts for millions of lost days at work and substantial economic losses to employers (Akazawa et al., 2003). Here, we aim to investigate the social dynamics that influence compliance with hygienic safety measures. In order to do so, we carry out a field experiment at the sites of a Belgian steel plant, with a total of 5500 employees, to investigate the influence of several behavioral interventions on hand hygiene. We set up interventions such as varying the position of hand sanitizers, increasing their visibility and by placing messages to encourage hand hygiene. Because group influences are very important in large industrial plants, we also assess whether there is a difference in the usage of the hand sanitizer when entering in group compared to people who pass by individually. Those insights can prove useful to support policymakers in minimizing the infection rates in both health and non-health organizations, and society as a whole.

Revising Safety Measures from a Boundedly Rational Behavioral Perspective

Next to vaccines, interventions implemented to slow down the spread of the coronavirus include hand washing and disinfecting, wearing masks in public, physical distancing, ventilation and eventually a variety of lockdowns, covering curfew, quarantines and travelling restrictions (Lunn et al., 2020; Meyerowitz-Katz & Merone, 2020). It became increasingly clear however that the expected compliance with the proposed more rational measures is complicated by a variety of human factors. From a social perspective, the perseverance of people is put to the test on respecting the corona measures, by demanding a reduction of social interaction, self-isolation, curfew restrictions, limited physical affection and the lack of leisure activities. This derogation of the social tissue is detrimental for the mental health of the population (Xiong et al., 2020). Both economic and social challenges complicate fostering and enforcing compliance with the imposed safety measures (McKibbin & Fernando, 2021).

It is therefore important to take a closer look at the behavioral and cognitive barriers that hamper compliance with the safety measures in more depth. Some people might have the intention to comply with the safety measures, to the extent that they find it reasonable, but fail to act accordingly. Other people might be ignorant or reluctant to compliance. What determines whether people decide to disinfect their hands, when arriving at the workplace, or not? Do people apply rational calculations about the infection rate at work? We know that humans are not always rational agents that optimize behavior, especially not in such a complex and unseen pandemic. Human decision-making is bound in its rationality and often works with heuristics that are prone to cognitive biases (Kahneman, 2011). Other influences such as the strong impact of human emotions result in decisions and actions that can differ strongly from our desired outcome; or the outcomes that governments consider desirable (Benartzi et al., 2017). According to the dual-process theory of decision-making (Kahneman, 2011), a relevant distinction can be made between two systems of thinking.

System 1 thinking is a more automatic, fast and unconscious way of thinking that requires little effort and is associated with no feeling of control. This is seen as an instinctive way of 'thinking' or decision-making, and includes subconscious values, drives and beliefs that influence our 'gut reactions'. Examples are the automatic actions when driving a car on an empty road, subconsciously linking a color to certain moods and mindlessly following the example of a group of people (e.g., looking up or suddenly starting to run). System 2 thinking is considered a more rational way of thinking and is associated with the subjective experience of power to act, choice and concentration. It includes conscious attention for the mental effort that is being done. Examples are trying to remember something, comparing the price-quality of products and focusing attention in a noisy room. Behavioral interventions that address system 1 assist in following through with the right intentions or that encourage the desired behavior by rearranging the social or physical environment. This approach, also referred to as 'nudging', acts upon various often-overlooked aspects of human behavior, including its bounded rationality, in current safety measures and is a valuable complementary component of current behavioral change strategies.

The Concept of Nudging

The idea that humans are boundedly rational has given rise to a series of psychological studies investigating how behavior can be influenced through by modifying contextual, often subconscious, factors. Thaler and Sunstein (2008) put forward the concept of 'nudging', meaning literally 'to give a little push', to address this practice. They suggest that people can be guided and supported in making the right decisions to promote the more preferred behavior, by altering the choice architecture surrounding this behavior – i.e., the physical, social and psychological aspects of the context that influence our choices. A typical example of a nudge is a default opting-out procedure to promote organ donations (Davidai et al., 2012), which leverages the human tendency to minimize effort when indifferent to the outcome (de Ridder et al., 2022). Another example is the use of colorful footprints towards the stairs to promote stair climbing (Van Hoecke et al., 2018). This salient intervention draws attention to a certain desired action (i.e., stair climbing) suggesting it is the better choice to make in the given situation. The goal of these nudges is to counter undesired flaws in modern day decision-making, targeting evolutionary heuristics and cognitive limitations, to achieve the desired behavioral outcomes (Tversky & Kahneman, 1974). The application of nudges has been found successful in various domains, including health (Hanks et al., 2012), financial decision-making (Thaler & Benartzi, 2004), climate preserving actions (Bergquist et al., 2023) and education (Weijers et al., 2021), and can be an aid to a good health and safety policy (Dolan et al., 2012; Goldenbeld et al., 2016).

Effectiveness, Cost-Effectiveness and Ethical Concerns

A recent meta-analysis by Mertens and colleagues (2022), including more than 200 studies, concludes that overall choice architecture interventions (or nudges) promote behavioral change with a small to medium effect size (Cohen's d = 0.45). Other studies, including data from governmental nudge units (DellaVigna & Linos, 2022) and controlling for publication bias (Maier et al., 2022), call for caution and indicate that expected effect sizes are likely to be lower. Hallsworth (2022) adds that the goal should be to assess the effectivity of nudges in specific contexts, rather than to summarize the effectiveness of nudges in its entirety; which may lead to inaccurate and irrelevant conclusions. Context dependency is key for nudge interventions and should encourage research to define the crucial influencing environmental factors. In addition, the long-term effects of nudges have barely been studied and the few studies show mixed results (Brandon et al., 2017; Marchiori et al., 2017; Van Rookhuijzen et al., 2021). It appears to be dependent on both nudge types and implementation context, which again highlights the importance of a fine-grained analysis of the contextual moderators.

One of the biggest advantages of using nudge interventions is their cost-effectiveness in comparison to typical intervention methods such as financial incentives. Indeed, Benartzi et al. (2017) report that government nudges often yield particularly high returns at a low cost when it comes to boosting retirement savings, college enrolment, energy conservation, and vaccination rates. For example, $1 spent on retirement saving interventions resulted in an increased contribution of $100 for nudges, compared to $14.58 for information campaigns and $1.24 for tax incentives. These findings suggest that nudging interventions could be of great value to improve the cost effectiveness of behavior change programs in public and private organizations, including public health policy.

Nudging has also sparked debates concerning ethical issues and whether it is legitimized to alter people's behavior in often-covert ways without consent of the affected individuals (Lin, Osman & Ashcroft, 2017). Sunstein (2015) concludes that when nudges fall within the periphery of the concept of manipulation (i.e., not the strongest forms such as lies), when they have legitimate purposes, when they would be effective, and when they do not diverge from the kinds of influences that are common and unobjectionable in ordinary life, that the burden of justification often can be met. Also, it is impossible not to have a choice architecture. For instance, regarding placement of alcohol gel dispensers, it has to be placed somewhere. Optimal placement may be a nudge, but suboptimal placement is also a nudge relative to the optimal position, be it in the wrong direction from a health optimization viewpoint.

Nudging Hand Hygiene

Prior to COVID-19, hand hygiene was already particularly important for hospitals, as HAIs can be detrimental or fatal for patients with a weakened immune system (Boyce & Pittet, 2002). Hand hygiene is considered one of the primordial factors to combat HAIs (Jefferson et al., 2009). Aaerestrup and Moesgaard (2017) examined how hospital visitors can be nudged to comply with hand hygiene protocols. They found that nudge interventions focused on the placement of the hand sanitizers, colorful indications and social norm messages (i.e., informing about what people do or find important) were successful in promoting hand hygiene. These findings were replicated in more recent studies in hospitals with larger sample sizes (Mobekk & Stokke, 2020; Hansen et al., 2021). A systematic review on nudge effectiveness promoting hand hygiene found that nudges were overall effective, but included mainly studies in hospitals and schools, and only one in a shopping street and a military base (Gof, 2022). These results are encouraging in the light of a pandemic, and for controlling viral viruses in general, as they provide guidance of how we could successfully improve hand hygiene in a non-health private organization using nudge interventions. More closely to this topic, Van Dessel and colleagues (2022) found nudges (i.e., placement plus red sign 'Please disinfect hands', and posters with elderly 'Disinfecting hands saves lives. Will you disinfect your hands?') to be effective in promoting hand hygiene among visitors of a supermarket. A remaining question which we address in the current study is whether these interventions can be successful in contexts such as the daily workplace, especially contexts in which health and hygiene is not very apparent, like industrial plants. The clear distinction of the effect of hygiene nudges between environments where hygiene is less apparent (e.g., industrial plants), compared to environments where hygiene is more apparent (e.g., hospitals, schools, food stores), is hardly investigated. In addition, most nudge studies focus on visitors, while more research among employee populations is needed (Gof, 2022).

Friction and Salience

Some choice architectural elements used in previous nudge studies, including those promoting hand hygiene, form a valuable basis for this study. Friction is one of those concepts often used for effective behavior change. This concept was first described in the 19th century by Guillaume Ferrero as 'the Principle of Least Effort' (1894), stating that if humans are presented with multiple paths for any decision, they will inevitably pick the easiest. Metcalfe et al. (2020) found that the mere placement of healthy food in school cafeterias affected the food selection and consumption of the pupils, and Houten et al. (1981) nudged participants to take the stairs by increasing the waiting time of the elevator by 16 sec. By strategically placing hand sanitizers and reducing friction, an increased usage of alcohol gel could be expected, as found in the hospital studies (Aaerestrup and Moesgaard, 2017).

Another relevant aspect includes altering the salience of the alcohol gel dispensers. Salience is described as that property by which some things stand out compared with its surroundings. It captures the capacity of something in the environment to catch and retain one's attention (Taylor & Thompson, 1982). A better placement of the hand sanitizer increases the visibility and might be more salient. As an example of the versatile ways in which salience can be increased, Hansen (2011) found that the use of green footstep prints towards trash cans reduces littering. He argues that increased salience is an important aspect of behavior change interventions and that the presence of stronger social norms could moderate the salience effect. This means that the stronger a certain behavior is considered as 'desirable', the stronger the effect can be of salient interventions drawing more attention to these specific actions.

Group Behavior and Social norms

People are easily influenced by their social context. How others behave or what they value (i.e., social norms) has a strong impact on the individuals' belief and behavior. Research has shown that the behavior and attitudes of others can be contagious, either by the thought of missing information that the group must have (i.e., social proof; Cialdini, 1993, 1999) or by the need to belong to a group, based on the fear of being expelled, which can lead to conformity[2] (Ash, 1956). In the light of the COVID-19 pandemic, the apparent impact of social influences is shown in recent occurrences, such as global panic buying in retail (Prentice et al., 2022) and international stock market inefficiencies (Aslam et al., 2022). Both examples are generated by contagious behaviors and expectations, and stress the possible consequences of herd mentality and herd behavior[3] (Banerjee, 1992). Studies in several domains, including health and finance, use insights in those social dynamics (i.e., herd behavior, conformity and social proof) to implement behaviorally informed social interventions (Allcott, 2011; Bikhchandani & Sharma, 2000; Lindhout & Reniers, 2017). The same social dynamics should be considered when developing safety interventions to combat infectious diseases (e.g., promoting hand hygiene), especially during a pandemic.

During the pandemic clear expectations have been communicated by the government and employers regarding safety measures (Brauner et al., 2021; Talic et al., 2021), and relatives and colleagues express their opinions and values to a certain degree. In this way, behavior such as hand hygiene compliance can become strongly subjected to social norm influences. Social norm nudges provide feedback on one's actions compared to a reference group[4] and have proven particularly effective in promoting pro-environmental behavior (Farrow et al., 2017; Bergquist et al., 2022). Social normative feedback can either be descriptive, representing what most people actually do to allow impactful comparisons (e.g., "the majority of guests reuse their towels" in Goldstein et al., 2008), or injunctive,

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[2] Conformity is the act of matching attitudes, beliefs, and behaviors to group norms to avoid rejection (Ash, 1956).
[3] Herd behavior refers to people acting in the same way as others are doing, instead of using their own information or by making independent decisions.
[4] Reference groups refer to any group that is used by an individual as a standard for evaluating themselves and their own behavior (Bicchieri, 2017).

communicating what behavior others approve or disapprove (e.g., "Please don't remove the petrified wood from the park" in Cialdini et al., 2006). According to Cialdini (2013), injunctive norms are often more effective when the undesirable behavior is more prevalent than the desirable behavior. In a health context, social norm messaging has proven effective in promoting hand hygiene among hospital visitors (Mobekk & Stokke, 2020). The question remains whether the effect maintains in an environment, such as a steel industry plant, where social norms towards hand hygiene are less strong and explicit.

CURRENT STUDY

According to studies in hygiene-focused environments, including schools and hospitals (Jefferson et al., 2020), proper hand hygiene reduces acute respiratory infections (ARIs) and absenteeism by up to 16% and 36%, respectively. Hospital studies suggest health-promoting nudges can enhance hand hygiene compliance by around 55%, leading to an approximate 8% ARI reduction and a 16% decrease in absenteeism. As COVID-19 and seasonal flus impact the broader population, more research, especially in under investigated less hygiene-centric organizational settings, is needed to assess the effectiveness of behavioral interventions in reducing workplace absenteeism and preventing hospitalizations (Mirzadeh & Khedmat, 2022; Liu et al., 2021). For this end, a large-scale field experiment is carried out at the Belgian site of the multinational steel factory during the pandemic (June – August 2020). Here, we aim to examine if nudge effects hold in a context where health and hygiene is less apparent and that involves mainly employees instead of visitors (e.g., successful hand hygiene nudges in supermarkets, Van Dessel et al. (2022)), often overlooked in nudge studies (Kubera, 2023) (RQ1). To address this issue, multiple nudge interventions are developed and implemented on the site of the steel company.

The first nudge intervention focuses on the placement of the hand sanitizers. By doing this we alter the required amount of effort to perform the action, which is often referred to as a reduction of friction (Popova & Popov, 2015). By making the action easier to perform, even slightly, an increase of the desired behavior is likely to occur. In accordance with similar behavioral studies manipulating friction to promote healthy food, consumption and hand hygiene in hospitals, we expect this intervention to have a moderate effect on hand hygiene compliance at the industrial plant (Hypothesis 1). A second intervention focuses on salience by placing green footstep prints towards the hand sanitizer. This should redirect the attention to the hand sanitizer more explicitly and increase its weight on the decision to comply or not. A small positive effect on hand hygiene compliance is expected (Hypothesis 2), as was found in previous studies with salient footstep prints in the context of littering (Hansen, 2011) and the use of stairs (Van Hoecke et al., 2018). A third intervention is a displayed message relating to the elaborated concept of social norms (Bicchieri, 2017). By providing information about what others do (i.e., descriptive norms) and approve (i.e., injunctive norms) regarding the use of the hand sanitizer, we aim to highlight good examples and values, and to evoke social influences promoting hand hygiene. The use of social norm messages proved successful in improving hand hygiene in hospitals (Mobekk, 2020). Here we expect a positive effect of social norm messaging, but smaller than in the hospital environment, as compliance with hand hygiene and its potential consequences carries a lower weight in the current industrial context (Hypothesis 3).

In addition, we aim to study if the appearance in group influences the usage of the hand sanitizer (RQ2), taking in consideration the relevant insights of herd behavior (Le Bonn, 1899; Economou et al., 2018; Lin, 2018). Here, we expect that people in group become more aware of potential moral condemnations and therefore become more sensitive for guiding social cues (i.e., social norm messages and behavior of group members) and tend to conformity (Banerjee, 1992), increasing the usage of the hand sanitizer (Hypothesis 4).

METHOD

Participants

In this study, carried out in a natural industrial setting, we observed all employees passing by the main entrances in the Administrative Building (AB) of the steel plant. During the two months of our research, 861 separate employees worked at the AB, excluding those who worked remotely. Of this group, 74% identified themselves as male (N= 639) and 26% as female (N=222). The male group had an average age of 48 years old (*M*= 48.2, *SD*= 10.6), compared to an average age of 46 years in the female group (*M*= 46.3, *SD*= 8.7). The members of both groups had a predominantly Belgian nationality, respectively 98% and 95% for the male and female group. Most of the employees working at the AB are white-collar workers, with a small share of blue-collar workers (<5%). Before starting this study, approval was obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are free accessible for the employees on the intranet website of the steel plant. Ethical clearance for this study was provided by the safety department of the industrial plant.

Research Design

In this field experiment, we use a mixed design incorporating within-subjects evaluations per location and between-subjects comparisons between locations, including multiple control groups (see overview Table 1). Five locations at the AB were selected with the highest number of passersby. This included three main entrances to the building (*Gate 1-3*), the sandwich bar (*Gate 4*) and one entrance to the restaurant (*Gate 5*). A variety of interventions was assigned to each location, including pre- and post-tests. Except for the control location, each location contained a varying combination of the interventions but in a different order to partially counterbalance sequence effects. The experiment lasted 7 weeks in total. *Gate 5* functioned as a control measurement. No interventions were implemented here. Because of worsening corona conditions and governmental measures, reasons unrelated to the experiment, this location had to close in week 6. Therefore, several control measurements were done at other locations, removing active interventions for a week, to see if the effects would decrease or persist. In the other gates (*Gates 1-4*), the control condition and Intervention 1 lasted for two weeks, while other interventions lasted at least 1 week.

Table 1

The sequence of the nudge interventions per location

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7
Gate 1 (camera footage)	Control	Control	Placement	Placement	Placement Social norm	Placement Social norm Footsteps	Control
Gate 2 (camera footage)	Control	Control	Placement	Placement	Placement Footsteps	Placement Social norm Footsteps	Placement Social norm Footsteps
Gate 3	Control	Control	Placement	Placement	Placement Footsteps	Control	Placement Footsteps
Gate 4	Control	Control	Placement	Placement	Placement Social Norm	Placement Social Norm	Placement Social Norm
Gate 5	Control	Control	Control	Control	Control	/	/

Note. Gate 1 = 'Main entrance Wing 5'; Gate 2 = 'Main entrance 2; Gate 3 = 'Main exit; Gate 4 = 'Sandwich bar'; Gate 5= 'Restaurant'; Control = 'Original position of hand sanitizer'

Materials and Procedure

We test the effect of the mere placement of the dispensers (see Figure 1), removing them from the wall and placing them on a pillar in the middle of the entrance (see Figure 2), making it more visible and less effortful to use the dispenser. The same manual dispensers are chosen that hung up already, requiring a horizontal push to use it. Every location has the same type of dispenser. Using a new, hands free, dispenser could have influenced the behavior of interest and thus the results of the experiment.

For this reason, four stable stands are crafted at the central workshop of the industrial plant with weighted bases to resist the impact of horizontal pushes. For the second intervention, we add a sign with a social norms message ("Here we use ALCOHOL GEL to protect each other", in Dutch) on a green background (see Figure 3). A potential unintended effect of social norms messaging occurs when the message emphasizes the majority of people performing the undesired behavior. A message displaying that 30% of the people comply with the rules, triggers thoughts of 70% doing the opposite (Cialdini et al., 2006; Goldstein et al., 2008). As we estimate the initial compliance rate to be rather low, we decide to keep the message more abstract by not providing any percentages. Mentioning the 5% baseline level of compliance at the administrative building of the steel plant could have been detrimental for the effectiveness of this intervention. A third intervention is the use of salient green footstep prints on the floor heading towards the alcohol gel dispenser (see Figure 4). For this purpose, we used ground stickers that can be placed easily on the ground and were robust. At last, we test a combination of all three nudges, including placement, salient footsteps and a social norms message (Figure 5).

Figure 1

Original placement of the hand sanitizer (Control condition)

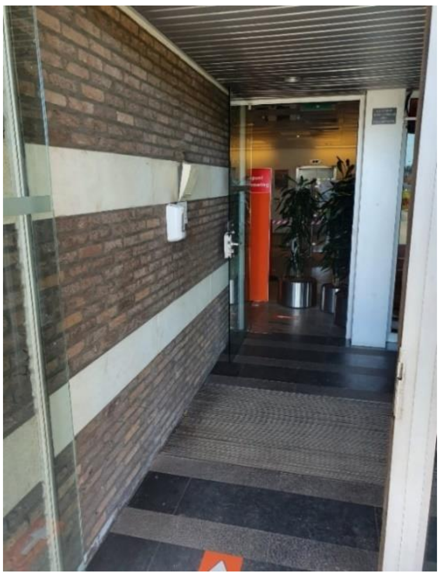


Figure 2

The mere placement of the hand sanitizer on a pillar (Intervention 1)

Figure 3

The placement of the hand sanitizer on a pillar with a social norms message (Intervention 2)

Figure 4

The placement of the hand sanitizer with salient footprints (intervention 3)

Figure 5

The placement of the hand sanitizer on a pillar with a social norms message along with salient footprints (Intervention 4)

Observation Method

Two observation methods were selected: alcohol gel consumption (in ml) and camera footage.

Alcohol Gel Consumption

At all locations, changes in the volume of the dispensers were measured. This provided us with information on how much alcohol gel had been used exactly at each of the five location. From this we could deduce and estimate how many of the passersby disinfected their hands. To make an accurate estimate two things needed to be assessed, namely the number of pushes per individual while using the dispenser and how much milliliter of alcohol gel one push contains. A preliminary observation has been carried out to check the number of pushes. From the 100 people observed, 97 pushed the dispenser one time, the other 3 persons two times. Based on this observations, the assumption was made that one person would push the dispenser one time in most cases during the experiment. Camera footage was used to double check as will be discussed later. To assess the volume of one push, the average was taken of 50 pushes. The average volume of one push was 1 ml. The consumption of the alcohol gel was measured at each location twice a week, at Wednesday and Friday evening at 19h. To determine the number of passersby data was collected from the electric gates, which people need to pass to enter, together with camera footage.

Camera Footage

At specific locations, including *Gate 1* and *Gate 2,* camera footage was used. This allows us to make observations that are more accurate and to double-check the reliability of the alcohol consumption method. Specifically, we used this data to investigate social effects, usage in group or individually, and the difference between different time slots (07h00 – 11h00; 11h00 – 15h00; 15h00 – 19h00). In this way, data from more than 14 000 observations is collected during the experiment across all locations. In-person observations were not appropriate because of the time-consuming nature, the impossibility to observe multiple places simultaneously because of lack of additional observers, and the potential impact on the participants' behavior. The approval for using cameras is obtained from employee unions and the management of the industrial plant on condition that the privacy of the employees would be strictly protected.

Data Analysis

We use the ordinal least squares (OLS) method to investigate the effect of the nudge interventions on the alcohol gel consumption, along with the mere effect of the time periods (i.e., 'Monday-Tuesday-Wednesday' and 'Thursday-Friday') and locations on the consumption of the alcohol gel. The usage (in ml) per passerby is the dependent variable, while the interventions, time periods and locations served as predictors.

To attain a deeper insight into the usage of the alcohol gel dispenser a logistic regression (LR) was conducted to analyze the dichotomous data of dispenser use (1= used, 0= not used) collected using the camera footage. These results do not only provide us a more detailed insight in the effectiveness of the nudges, but also allow us to investigate the effect of social dynamics in influencing the usage of the alcohol gel dispenser. More specifically, we measure the effect on usage by the participants being in a group or not and whether or not the first person used the dispenser. In addition, the effect of individual weekdays (i.e., Monday, Tuesday, Wednesday, Thursday and Friday) and specific time intervals per day (i.e., 'Morning' = 07h00-11h00, 'Noon' = 11h00-15h00, and 'Afternoon' = 15h00-19h00) are assessed. The Odds-ratio (OR) is used to facilitate the interpretation of the probabilities of the dichotomous outcome variable. The OR is a measure of association between exposure and outcome. It represents the odds that an outcome will occur given a particular exposure, compared to the odds that the outcome will occur without that exposure. All analyses were performed in IBM SPSS Statistics for Windows, version 27 (IBM Corp., Armonk, N.Y., USA).

RESULTS

Ordinary Least Squares (OLS) Regression – Alcohol Gel Consumption

Table 2 displays the results of the first part of the OLS regression analysis, including the effect of the nudge interventions, time periods (i.e., 'Monday-Tuesday-Wednesday' and 'Thursday-Friday') and locations, for the alcohol consumption method. The results of the OLS regression show us that all the intervention conditions have a statistically significant result on a 0.01 level ($p < .01$).

In the control condition, the dispenser was used in 7% (N=993)[5] of the opportunities observed (N=13820). In the placement and placement-footsteps condition, the dispenser was used in 27% (N=2434) and in 47% (N=1125) of the 2393 and 3075 observed opportunities respectively. For the placement-message condition, the dispenser was used in 45% (N= 1384) of the observed opportunities (N=3075), and in the placement-message-footsteps condition the dispenser was used in 57% (N= 1613) of the observed opportunities (N=2830). See Table A1 in Appendix 2A for a more detailed overview of the number of passersby and the alcohol gel consumption (in ml) per condition. Passersby in the placement condition are 21% more likely to use the alcohol gel dispenser when compared to the baseline. Passersby in the placement-message condition, in the placement-footsteps condition and the placement-footsteps-message condition respectively have a 46%, 38% and 54% higher probability of using the alcohol gel. The regression model additionally incorporates the second time period (i.e., 'Thursday-Friday'). The results reveal that the passersby in the have a small lower chance of 3% using the dispenser when compared to the baseline (i.e., 'Monday-Tuesday-Wednesday'), but these results are not significant. Next to nudging interventions and days-of-the-week effects, the model also controls for the locations of dispensers. Estimation results indicate that passersby at the locations *Main entrance Wing*

[5] Note that this number represent the usage in ml. Given that pre-observations determined that 97% of the participants pushes one time and that one push equals 1ml, we use the usage in ml as an estimate of the number of individuals who used the dispensers.

5 ('Gate 1') and *Main entrance 2* ('Gate 2') are respectively 8% and 15% more likely to use the alcohol gel, when compared to the baseline measure, here *Main exit* ('Gate3'). People that passed by at the locations *Sandwich bar* ('Gate 4') and *Restaurant* ('Gate 5') were respectively 17% and 14% more likely to use the alcohol gel. Figure 6 provides an overview of the usage of the hand sanitizers (in ml/passerby) per condition.

Table 2

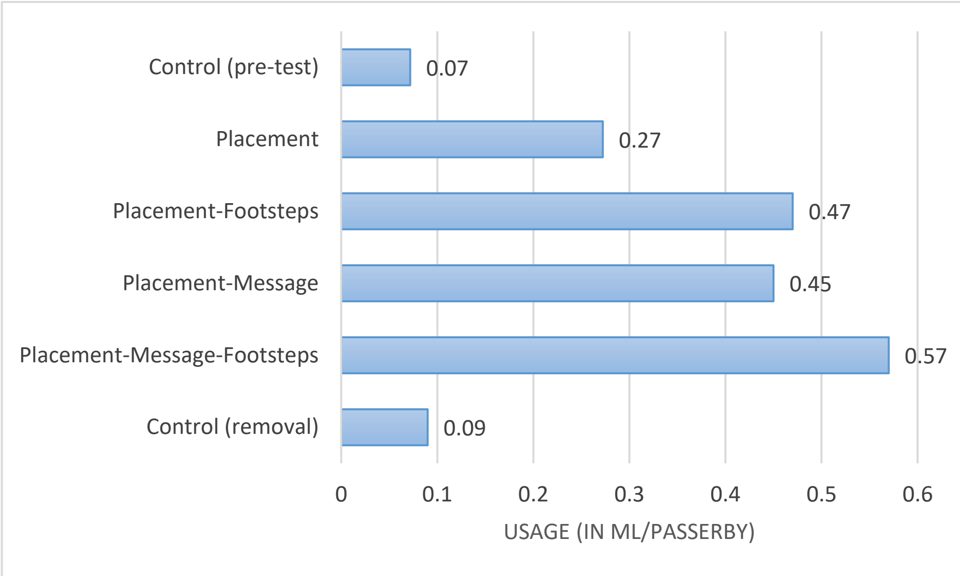
Results of the OLS regression analysis

VARIABLES	USAGE HAND SANITIZER	
	B	95% CI
Placement	0.213*** (-7.758)	0.16 - 0.27
Placement-message	0.417*** (-10.904)	0.34 - 0.50
Placement-footsteps	0.431*** (-10.715)	0.35 - 0.51
Placement-footsteps-message	0.516*** (-12.729)	0.43 - 0.60
Thursday-Friday	-0.025 (-1.230)	-0.07 - 0.02
Gate 1	0.078** (-2.329)	0.01 - 0.15
Gate 2	0.149*** (-4.514)	0.08 - 0.22
Gate 4	0.166*** (-4.571)	0.09 - 0.24
Gate 5	0.142*** (-3.612)	0.06 - 0.22
Observations	64	
R-squared	0.885	

Note. t-statistics in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control', days of the week 'Monday-Tuesday-Wednesday' and for gates 'Gate 3'.

Figure 6

The usage of the hand sanitizers (alcohol gel consumption)



Logistic Regression (LR) Analysis – Camera Footage

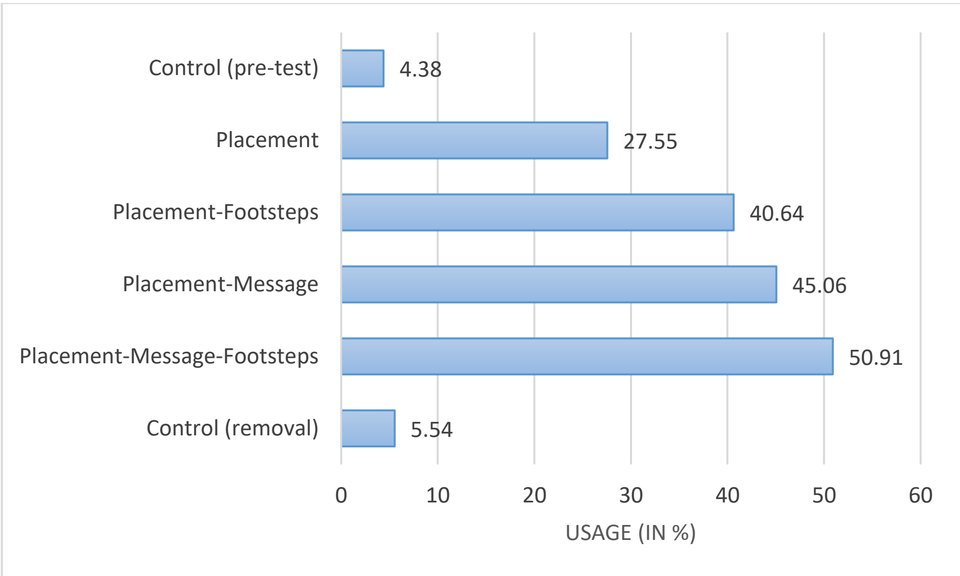
The results of the LR provides us a more detailed insight into the effects of the nudge interventions, including differences on daily basis (i.e., Monday, Tuesday, Wednesday, Thursday and Friday) or certain time period during the day ('Morning', 'Noon' and 'Afternoon'). The data collected based on the camera footage has a higher accuracy and can thus be used as a double check of the effects found using the alcohol consumption method. The cameras were only present at location *Main entrance Wing 5* ('Gate1') and *Main entrance 2* ('Gate2'), so the following findings only refer to these locations.

Nudge Interventions

A summary of the results can be found in Table 3. The results of the LR analysis show that all intervention conditions have a statistically significant effect on a 0.01 level (p < .01). In the control condition, the dispenser was used in 4% (N=7274) of the opportunities observed (N=326). In the placement and placement-footsteps condition, the dispenser was used in 28% (N=1141) and in 41% (N=321) of the 4142 and 789 observed opportunities respectively. For the placement-message condition, the dispenser was used in 45% (N=226) of the observed opportunities (N=502), and in the placement-message-footsteps condition the dispenser was used in 51% (N=987) of the observed opportunities (N=1938). See Table A2 in Appendix 2A for a detailed overview of the number of passersby and hand sanitizer usage per condition. The OR of the placement condition indicates that passersby in this condition were 7.7 times more likely to use the alcohol gel than in the baseline condition ('Control'). The OR ratio of the placement-footsteps condition, the placement-message condition and the placement-footsteps-message condition indicates that passersby were respectively 17.9, 19.8 and 20.4 times more likely to utilize the dispenser compared to the baseline condition. Figure 7 provides an overview of the usage of the hand sanitizers (in %) for all conditions.

Figure 7

The usage of the hand sanitizers (camera footage)



Weekday and Time of the Day

When checking for the effects of the before mentioned days of the week in Table 3, we see that each day presents a statistically significant effect. When taking Monday as the baseline condition, we see that the passersby at the other days are 12-19% less likely to use the alcohol gel dispenser. For Tuesday, Wednesday, Thursday and Friday, this is 12% ($p < .1$), 13% ($p < .1$), 15% ($p < .05$) and 19% ($p < .01$) respectively. The results also show us that the passersby in the morning, between 07h00-11h00, ('Morning') are 15% less likely ($p < .01$) to use the alcohol gel compared to the baseline, in this case the time period between 11h00 and 15h00 ('Noon'). People passing by between 15h00-19h00 ('Afternoon') were 41% less likely ($p < .01$) to disinfect their hands compared to the baseline.

Social Group Effects

The LR analysis also allows us to investigate how social influences impact the usage of the alcohol gel (Table 3). The results of the first model indicate that passersby in group ('Group') are 8.4 times more likely ($p < .01$) to use the dispenser than when they are not in group; controlling for the weekdays and daily time periods. The second model adds the variable 'Group 1st', which captures if the first person in the group did or did not use the dispenser. When we look at the results we see that passersby in group were 27.3 times more likely ($p < .01$) to use the alcohol gel when the first person used the alcohol gel, compared to when this person did not. In addition, we see that the group effect, observed in the first model, is no longer significant after controlling for the 'Group 1st'. This indicates that not the mere fact of being in group impacts the use of the alcohol gel, but that the group effect is likely to be mediated by the leading example of the first person using or not using the dispenser. This finding remain stable after controlling for weekdays and time of the day effects. Across both models, we observe that the intervention effects remain relatively stable and significant at a 0.01 level ($p < .01$). In a subsequent analysis, we found that people who are in a group with the first person using ('Group 1^{st}') were 2.5 times more likely ($p < .01$) to use the hand sanitizer compared to people who are in a group in general. Additionally, we found that people in a group with the first person using were 16.8 times more likely ($p < .01$) to sanitize their hands compared to individuals in a groups where the first person did not use the hand sanitizer.

Table 3

Results of the Logistic Regression (LR) analysis

VARIABLES	USAGE HAND SANITIZER			
	Exp (B)	Exp (B)	95% CI	Cohen's D
Placement	7.728*** (-30.05)	7.724*** (-30.045)	6.76 - 8.83	0.69
Placement-footsteps	17.896*** (-31.05)	17.891*** (-31.052)	16.02 - 24.36	1.08
Placement-message	19.781*** (-27.93)	19.755*** (-27.924)	14.91 - 21.46	1.13
Placement-footsteps-message	20.456*** (-41.204)	20.438*** (-41.198)	17.71 - 23.59	1.15
Tuesday	0.896 (-1.494)	0.9 (-1.430)	0.78 - 1.04	-0.07
Wednesday	0.859** (-2.182)	0.862** (-2.120)	0.75 - 0.99	-0.02
Thursday	0.832*** (-2.605)	0.835** (-2.549)	0.73 - 0.96	-0.02
Friday	0.763*** (-3.486)	0.773*** (-3.303)	0.66 - 0.90	-0.05
Morning	0.851*** (-3.314)	0.852*** (-3.262)	0.77 - 0.94	-0.05
Afternoon	0.592*** (-6.285)	0.601*** (-6.111)	0.51 - 0.71	-0.15
Group	8.363*** (-12.192)	0.543 (-0.977)	0.16 - 1.85	1.29
Group (first person)		24.012*** (-4.833)	16.62 - 37.15	1.58
Observations	14,645	14,645		

Note. Z-statistics in parentheses; *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control', days of the week 'Monday' and time of the day 'Noon'.

DISCUSSION

Next to the medical approach, it became clear that human behavior is a vital factor to temper a pandemic by an infectious virus like COVID-19 (Bavel et al., 2020). Yet, successfully attaining desired changes in behavior is proving difficult. Therefore, evaluating the effectiveness of behavioral interventions in controlling the spread of the coronavirus, and in extension for other viruses, such as the season flu, in both health and non-health environments, is undeniably necessary (Jefferson et al., 2020).

Nudges Promoting Hand Hygiene: Friction, Salience and Social norms

Reducing friction is one of the most straightforward, yet also one of the most underutilized behavioral change techniques. Sunstein (2022b) also refers to the term 'sludge' to name excessive frictions that needlessly prevent people from doing what they want or should do. Thaler (2021) adds that removing or reducing barriers could be more productive than trying to overcome them. This can be seen as the urge of humans to follow the path of least resistance and convenience, driven by system 1, that is only deviated from for good reasons by the intervention of System 2 (Kahneman, 2011). Our findings fall in line and reveal that the mere placement of the dispenser, clearly in sight and directly at the entrance, influences the hand sanitizing behavior of the passersby. These results validate previous studies showing that by simply altering the required effort, people can be nudged to consume healthier (Metcalfe et al., 2020), take the stairs more instead of the elevator (Houten et al., 1981) and to complete otherwise complex registration forms (Sunstein, 2022b).

By implementing salient green footsteps, we were able to draw the attention of the passersby and attain a small, but positive effect on compliance on top of the mere placement. Similar to the footsteps being used to reduce littering (Hansen, 2011), this study shows that these visual cues can be used to elicit the desired action, by increasing visibility. Together with the successful alterations in friction, these salient changes show how much the direct environment influences people at the specific moment they have to make a choice (Ischen et al., 2022). Kahnemann (2011) captures this in his acronym WYSIATI ('What You See Is All There Is'), referring to the fact that people make judgements or impressions according to the information that is available (i.e., availability heuristic), mainly driven by the automatic processing of system 1.

Through displaying a short social norm message, we implemented an additional environmental cue, providing information about the customs and values of the social environment (Bicchieri, 2017). The message contained both descriptive ('Here we use alcohol gel') and injunctive aspects ('to protect each other') and had a clear significant positive effect on hand sanitizing behavior. Being part of a group has always been important to humans, giving system 1 great weight to avoid potential social norm violations in our decision-making; an argument supported by brain response studies to social norms (Zinchenko & Arsalidou, 2018). Our findings show, together with a vast amount of studies in the literature (see Allcott, 2011; Bicchieri, 2017; Cialdini et al., 2006), that conveying social norm information in concise timely messages can successfully influence behavior.

The successful implementation of the hand hygiene nudges indicates the potential of behavioral interventions that respond to the underlying system 1. Large informational health campaigns, regulation and well-developed hygiene procedures are essential, but rely mainly on infallible logical processing of information (i.e., System 2). This study proves that a complementary approach, focused on designing good choice architecture using behavioral insights (including nudges), should be considered to overcome and assist psychological shortcomings in safety and health compliance.

Nudging Hand Hygiene in a Non-Health Organizational Environment

Previous studies found that nudge interventions can significantly promote hand hygiene compliance in hospitals (Mobekk, 2020). As the effectiveness of nudge interventions is heavily depending on the implementation context (Hauser et al., 2018; Sunstein, 2022a), the question remained whether the nudge interventions would also work in organizational environments where hygiene is less prevalent, unlike hospitals, schools and food stores (Gof, 2022; Hansen et al., 2021; Van Dessel et al., 2022). This study is among the first to investigate the effectiveness of nudges promoting hand hygiene in a non-health organizational environment and the findings confirm the effectiveness of hygiene promoting nudges in such contexts. This ties in with a debate regarding the practice of nudging. Recent studies found that the effectiveness of nudges can be smaller than expected when controlling for publication bias (DellaVigna & Linos, 2022; Maier et al., 2022). An important consideration here is that the expected effectiveness of nudge techniques in general can be very different from observed effects if the context is insufficiently taken into account (Hallsworth, 2022). For example, a recent study on the effect of salience on hand sanitizing in a shopping street found no effect of the intervention (Weijers & de Koning, 2021), whereas the current results in a factory and previous results in hospitals do show the effectiveness of this type of nudge. This shows that specific locations and contexts could act as a mediating factor. By testing the effectiveness of nudge interventions in heterogeneous domains, we can increase our understanding of the applicability of nudge techniques to promote specific behaviors like the disinfection of hands. Sunstein (2022) argues that the most important implication involves shifting to more targeted and personalized nudge interventions, which can produce higher welfare benefits than blind 'mass' approaches.

The Additivity and Cost-Effectiveness of Nudge Interventions

In our study, the combination of the nudge interventions lead to a higher increase in people disinfecting their hands in comparison to the isolated interventions. It appears that the effect of the nudges added up to a great degree, instead of cancelling each other out. This shows that both saliency and social factors may influence system 1 simultaneously and independently. In a study with much smaller effects, Brandon et al. (2019) also reported a smaller reduced peak load electricity consumption with isolated interventions (2%-4%) compared to a combination of interventions (7% reduction). They equally found additivity of the nudge interventions in subsequent applications and limited evidence of crowd out effects. Ayal and colleagues (2021) concur with this idea of additivity and found that combining visibility cues and social norms was more effective to orient people toward more moral behavior then separate interventions. The additivity of effects is of course even more important for nudging that yields smaller effect sizes (DellaVigna, 2022). If multiple nudge techniques can be combined to attain a cumulative greater effect, this would be of great value for policy makers and behavioral change practitioners trying to promote certain behaviors, including compliance with the hygienic safety measures.

Associated with the effectiveness of nudge interventions are the costs incurred for implementation. Benartzi and colleagues (2017) showed that simple nudge interventions were able to achieve significant results in a very cost-effective way, when compared to more classic policy instruments, including information campaigns and tax incentives. In this study the implementation cost were equally kept to a minimum. The total amount of the intervention costs added up to no more than 200 euros in total, excluding the organization cost of a limited number of necessary meetings. This allows us to make a rough estimation of the cost-effectiveness of our interventions regarding absenteeism. The absence rate during the winter period due to the seasonal flu at the steel plant is on average around 10%. We already mentioned that good hand hygiene can reduce absenteeism up to 36% (Jefferson et al., 2020) and that our combined nudge condition resulted in a 50% compliance rate among the 861 employees at the AB (i.e., 15.5 avoided cases). The median cost of a lost day at work for the industrial organization adds up to 300 euros/day for white-collar workers and the lost days per case of illness is considered to be three on average (Akazawa et al., 2003). This then results in an avoided cost of 13950 euro and a return on investment (ROI) ratio of 68 for every euro invested in implementing the nudges. This high ROI ratio aligns with findings of Benartzi and colleagues (2017) where ROI ratios added up to 100 for every dollar spent for nudges increasing retirement savings, while information campaigns and tax incentives attained a ratio of 14.58 and 1.24 respectively. A future careful analysis should be done to compare different hygiene promoting interventions (including nudges), regarding their cost-effectiveness, to further substantiate these findings.

Group Effects and Herd Behavior

Another important aspect of this research is the influence of the social dynamics on the usage of the alcohol gel dispenser. The findings provides interesting results concerning this matter, showing that people who pass by in group are significantly more likely to disinfect their hands, than people who pass by individually. However, this effect is mediated by the leading example of the first person in the group. It appears that the behavior of the first person in the group largely determines whether the other will use the dispenser or not. This is a clear example of herd behavior where passersby assume that the example of the person in the front of them is the way to go (Banerjee, 1992). They might believe that the person or people in front of them know(s) something that they are not aware of, concerning the necessity to comply with the safety measure or not. It could also be possible that the passersby following the example fear the possibility to be rejected by the group and conform to avoid this threat, leaning towards conformity (Ash, 1956). In addition, the dimension of social proof could be at play and is strongly related to the concept of herd behavior. This is defined as an informative social influence that can lead to herd behavior. Seeing how others behave in ambiguous situations where we are uncertain might provide information or cues in guiding actions (Cialdini, 1993). In this case, individuals who are not familiar with the new situation might take the behavior of the first person as a guidance for appropriate action. For the reason that the effect remains stable over the weekdays, it might be more plausible to assume that people follow the example because they want to avoid accusations from the group, than that they do not know how to act in the specific situation.

Time and Day of the Week Effects

Interestingly, we see that passersby are more likely to use the alcohol gel on Monday, than on the other days of the week. An explanation might be that people start their week with fresh energy and good intentions, but that this diminishes as the days go by. This idea is further supported, as the odds of using the alcohol gel lowers when days of the week pass by; with the lowest probability at Friday.

This is in line with the concept of ego depletion. The ego depletion theory indicates that self-control draws from a finite pool of cognitive resources. When the pool of cognitive resources declines, so does self-control (Kahneman, 2011), and therefore also the reliance on System 2, in favor of system 1 thinking. Another finding is that people are more likely to use the dispenser at noon, between 11h00 – 15h00, which might be an anticipation of people getting their lunch. If the virus possibly finds their way to the hands of the people, they might have the reflection to disinfect their hands before bringing them to their mouth to eat. Another explanation might be that people are less subjected to time pressure during the lunch break to comply with the safety measures, while during the morning (7h00-11h00) or afternoon (15h00-19h00) they might be more in a rush. Although nudge interventions influence the odds of people performing a certain behavior, certain factors remain likely to moderate its effectiveness, including cognitive load (Carroll et al., 2018; Sweller, 1988). In this case, time pressure could reduce the effectiveness of the nudge interventions, but still invoke a relative smaller reduction then in a situation with more System 2 interventions (e.g., training or campaigns). Referring back to the concept of ego depletion, we actually would expect here that nudge interventions experience a relatively smaller reduction in effectiveness because it draws on less cognitive resources then typical System 2 interventions (Kahneman, 2011).

Long-Term Effectiveness

An important and insufficiently investigated aspect of nudging is the long-term effect of the interventions (Marchiori et al., 2017). Our findings show that the effectiveness of the nudges maintained for several weeks and that the effect almost completely disappeared after removing the nudges (i.e., drop to pre-test level). This entails two things. First, it shows that the within-subjects design (sequence of interventions) is not the driving force behind the large effect sizes in the consecutive conditions. Secondly, it show that the hygiene nudges in this study have no long-term effects on behavior after the nudges are removed, and thus most likely not on attitudes (related to health and hygiene). Previous studies have shown that some interventions can have a long-lasting effect on behavior even after removing the nudges, such as the continued climbing of stairs after the closing time of the elevator was lowered to the pre-test level (Houten et al., 1981). More research is needed to identify which factors, related to the nudge approach, could lead to effective habit formation; including the necessary number of repetitive actions (not equal to intervention duration), the role of the implementation context and the features of the desired action (Wood, 2019).

Limitations and Further Research

For this research, a large field experiment was conducted at the steel plant. An advantage of field studies is that the findings have a high ecological validity (Meyer, 1995). Because of the high ecological validity, the chances are higher that our e can be replicated at different, but similar, real life settings. Field experiments, on the other hand, tend to have a generally lower internal validity. For this reason, a well thought out experimental design was used, including pre- and posttest, control measures and high number of participants (n= 861, 14 645 observations), to control for these confounding influences to the greatest extent. Further research should integrate both controlled (e.g., laboratory or online) and more ecologically valid methods (e.g., field experiments and 'mega studies', which are massive field experiments, see Milkman et al. (2021)) to support each other's deficiencies and further substantiate our findings. This aligns with Beshears and Kosowsky (2020) highlighting the need for both approaches to advance the field of nudging.

Another limitation of this study is that it is unclear how peripheral characteristics of the nudging interventions, such as the color of the footsteps or message, could influence the result (note that Aaerestrup and Moesgaard, 2017, had similar results with red messages). Likewise, given limited resources (i.e., available locations, time restrictions), we only tested one variation of the message being displayed right above the dispenser. Future exploration of different nudge formats (e.g., different colors and a variation of social norm messages) can bring additional value to the current findings.

Subsequently, our findings do not allow to draw conclusions on the long-term effects of the interventions (i.e., >3 months later). Some of the nudge interventions' effects, in general, have shown to decrease over time (Allcot & Rogers, 2014). We were able to show that the effect of the interventions maintained for several weeks and that the effect disappeared completely after nudge removal. Yet, a follow-up after a couple of months was intended, but not possible due to the rapidly changing governmental policy and business environment (e.g., mandatory remote work) due to the pandemic.

Further research should aim to refine which types of nudges work for promoting hand hygiene in which settings and under which circumstances. The organizational context, for example, both present in this study and the hospital studies, but not in the shopping street where similar interventions proved ineffective (Weijers & de Koning, 2021), could play a role in the nudge effectiveness. Michael Hallsworth (2022) highlights that having an eye for different effects in different environments with different cultures and demographics, rather than merely generalizing conclusions across different contexts and populations, is necessary to advance the field of behavioral science (incl. nudging) and to overcome distorted interpretations regarding nudge effectivity.

CONCLUSION

This study investigates the effectiveness of nudge solutions for the rapid surging infection rates during the coronavirus pandemic. More specifically, nudge interventions were developed and tested for the first time to promote hand hygiene in a non-health private company context. A large field experiment was conducted at the sites of a multinational steel plant, investigating nudges that would increase the number of people disinfecting their hands at the main entrances. The nudge interventions included the placement of the alcohol gel dispenser, a social norms message and footsteps placed on the ground. All interventions contributed significantly to an increase in the usage of the alcohol gel dispensers by the passersby. In addition, our findings show that people passing by in group have a significantly higher probability of using the alcohol gel than when they passed by individually. This effect was largely determined by the first person in the group using the alcohol gel dispenser. The nudge approach proved successful to promote hand hygiene in heterogeneous environments, including a non-health private company context, and provides guidance to combat contagious viruses, such as the coronavirus and the seasonal flu.

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CHAPTER 3

NUDGING SAFETY BEHAVIOR IN THE STEEL INDUSTRY: EVIDENCE FROM TWO FIELD STUDIES[1]

The practice of nudging received much attention in different domains of human behaviour (e.g., finance, health, traffic safety and sustainability), but its relevance has not been systematically investigated for safety in the process industry. This study aimed to investigate the effectiveness of nudge interventions in promoting safety behavior in the steel industry through field experiments in a large steel plant, particularly in relation to gas hazards and falling from stairs The results of both experiments showed that the nudge interventions were very effective in promoting safety behavior among workers. An icon reminding of the gas dangers on work jackets effectively increased gas detector compliance, while hand print cues were able to promote workers holding onto handrails. Related organizational implications for a safety nudging approach are discussed. Overall, these findings suggest that nudge interventions can be a cost-effective approach to promote safety behavior in the steel industry. The suggested nudge framework should be implemented as part of a holistic safety approach to promote safety behavior among workers and prevent severe accidents.

Keywords: Nudging; Safety Behavior; Process Industry; Gas Hazards; Staircase Safety; Field Experiment; Decision-Making

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[1] Costa, S., Duyck, W., Van Wouwe, E., & Dirix, N. (in press). Nudging Safety Behavior in the Steel Industry: Evidence from Two Field Studies. *Safety Science*

INTRODUCTION

Unsafe working environments imply a great human and economic cost. Starting in the fifties of the previous century, safety awareness has risen and incident rates in the process industry have known a remarkable decrease thanks to the introduction of improved technologies and safety standards. In the seventies, an increased focus on risk assessment and mitigation followed (Hudson, 2007), most often approached by a more technical perspective. Although these interventions were able to significantly reduce the number of accidents (CDC, 1999; Weeks, 1991), much room for improvement remained, and an additional focus on safety behavior and the safety culture was needed. How to effectively change the unsafe behavior of the employees still remains a complex issue and is raised by several experts as the last remaining challenge to resolve (Hopkins, 2006; Knegtering & Pasman, 2009; Lindhout & Reniers, 2017; Reason, 2009). Although concepts as 'prevention through design' might reduce accidents in some parts of the industry, a change in unsafe behavior would be able to eliminate nearly all occupational accidents. Therefore any further reduction of the accidents would require a more thoroughly understanding and control of the underlying behavioral component of safety (Bhattacharjee et al., 2011; Krause, 2001; Talabi et al., 2015). Research shows that up to 90% of the occupational accidents are human error related (Kletz, 2001). Addressing the human behavioral factor is therefore the biggest challenge for safety management today.

In the last decades, studies have brought new insights in human behavior, showing that people do not always act logically and with consideration, nor that they always make decisions in a fully rational way (Kahneman, 2011; Simon, 1955). The conception that people are 'boundedly rational' in turn led to the idea that people may benefit from a behavioral context that exploits automatic and suboptimal behavioral biases. This includes the implementation of subtle behavioral pushes, known as 'nudges', that strategically change the choice architecture (i.e., the physical, social and psychological aspects of the context that influence our choices, Thaler et al. (2012)) to change behavior, instead of focusing solely on rules, economic incentives, knowledge transfer and training (Thaler & Sunstein, 2008). Here, we want to apply the core insights of bounded rationality within behavioral science to industrial safety behavior, which to this day remains little explored (Lindhout & Reniers, 2017).

This unique field study takes place in a large Belgian steel plant that is familiar with the evolution and the current challenges concerning safety in the process industry. Although the incident rate dropped significantly over the years following classical and state-of-the-art safety approaches, their efforts seemed to have reached a plateau of a seemingly non-reducible number of safety incidents. In this study, we aim to investigate whether nudge interventions and choice architecture constitute an effective and supplementary safety management tool that complements the current classical safety approach. To this end, we developed and tested nudge interventions in safety domains that frequently encounter incidents in the steel industry, namely fall and gas hazards.

Two Systems of Decision-Making and Nudging

Actions can stem from deliberate, conscious reasoning or from automatic, unconscious responses triggered by the environment. Kahneman (2011) terms this distinction as 'system 1 and system 2 thinking' or the dual-process theory of decision-making. System 1 involves fast, instinctive, and unconscious decision-making, driven by subconscious values and beliefs, such as quick answers to simple math problems or associating red with aggression (Tham et al., 2020). On the other hand, system 2 is a more rational, deliberate thinking process, requiring conscious effort and attention, such as remembering something or comparing product prices. Both systems are typically active, with system 1 providing constant automatic responses, while System 2 engages in more complex or unplanned situations.

Thaler and Sunstein (2008) put forward the practice of ‘nudging’, meaning literally ‘to give a little push’, as a way to leverage bounded rationality. They suggest that people may be guided and supported in making the right decisions by subtly altering the choice architecture in which the behavior occurs. Examples are the use of smaller plates, which lowers the number of (unhealthy) food consumption (Wansink & van Ittersum, 2013) or painting colorful footprints on the ground towards stairs to lower elevator use (Van Hoecke et al., 2018). Importantly, individuals retain the freedom of choice, but typically behavior changes as a function of simple, and often cheap, targeted choice architecture interventions. Nudge interventions have been studied and implemented successfully in several domains, including health and well-being, financial decisions, energy efficiency, eating behavior, work performance and so forth (Castleman & Page, 2015; Hanks et al., 2012; Johnson & Goldstein, 2003; Schultz et al., 2007; Thaler & Sunstein, 2008; Torgler, 2004).

The Effectiveness and Cost-Effectiveness of Nudge Interventions

Hummel and Maedche (2019) conducted a review of 100 primary publications and found that 62% of experimentally tested nudges had statistically significant effects on behavior, with a median effect size of 21%. Similarly, a recent meta-analysis by Mertens et al. (2022), including over 200 studies and 450 effect sizes, reported an overall small to medium effect size for nudge interventions (Cohen's d = 0.45). Some studies call for caution, including those from governmental nudge units (DellaVigna & Linos, 2022) and those that controlled for publication bias (Maier et al., 2022), and suggest that actual expected effect sizes may be lower. Hallsworth (2022) adds emphasis on the importance of assessing the effectiveness of nudges in specific contexts to avoid drawing general, but inaccurate conclusions.

The cost-effectiveness of nudges is another advantage of this approach. Benartzi et al. (2017) report return on investment (ROI) ratios for nudges that ranged between 10– 100 for every invested dollar, compared to 14.68 for campaigns and 1.24 for tax incentives. Nudge interventions can therefore be of great value in improving the cost-effectiveness of behavior change programs in public and private organizations, including safety management. Besides the financial ROI, they are also often easy to apply and implement.

The practice of nudging sparked a debate on ethical implications, as it often involves covertly influencing behavior without consent (Lin et al., 2017). Recurring objections to the practice are that it is based on paternalistic grounds, it is a threat for an individual's autonomy, and it is unclear in whose interest the choice architects operate (Grüne-Yanoff & Hertwig, 2016; Hansen & Jespersen, 2013). In response to these objections, Sunstein (2015) states that it is pointless to object to choice architecture or nudging as such, as choice architecture cannot be avoided. Either situation influences towards one behavior or another. It is reasonable to worry about or object to particular nudges, but not to nudging in general. Secondly, he argues that from an autonomy and welfare point of view nudge interventions are actually required. This because other interventions such as bans, taxes or other traditional interventions often impact an individual's autonomy more than nudge interventions do. In their FORGOOD framework, Lades and Delaney (2022) propose seven ethical dimensions to consider when developing nudges, including fairness, openness, respect, goals, opinions options and delegation. Typically, the practice of nudging is considered legitimized when behavioral freedom is preserved and when the outcomes benefit both the influencer as the person who is being influenced (Sunstein, 2015). In the case of work health and industrial safety, this is more straightforward, as employer and employee interests are aligned, towards the safety of the employee. Yet, for industrial applications, an ethical board should guard the ethical appropriateness of suggested objectives, nudge formats and associated observation methods. Also, it is important to engage employee representatives (e.g., unions) in the decision process, as was also done for this study.

Taxonomy of Nudge Interventions

A plethora of toolkits (e.g., MINDSPACE, EAST) and nudge classifications exist (e.g., Hummel and Maedche (2019), Beshears and Kosowsky (2020) and Hansen and Jespersen (2013). While they all provide their own unique contributions, one of the most comprehensive, yet uncluttered taxonomy of nudge interventions is the one developed by Münscher et al. (2016).

Münscher et al. (2016) categorize nudges, also known as choice architecture interventions, into three clusters, each targeting specific psychological barriers and encompassing various techniques (see Figure 1) (Mertens et al., 2022). The first cluster, 'decision information', leverages decision-related information by increasing its availability, comprehensibility, and personal relevance. Techniques include providing social reference information, like social norms, to reduce ambiguity and guide appropriate behavioral responses. For instance, a study by Allcott (2011) showed that households receiving letters comparing their energy consumption to similar neighbors reduced usage by 2%, comparable to the impact of traditional financial interventions. Other techniques in this cluster involve providing (direct) feedback (Cappa et al., 2020) or rephrasing informational messages in more simplified and personally relevant formats (Cappa et al., 2020; Mills, 2022).

The 'decision structure' cluster leverages the context-dependency of decision-making by modifying the format or arrangement of choices. Notable techniques include changing defaults, such as opt-out organ donor policies that significantly increase donor rates (Davidai et al., 2012). Crucial seems to be the effort people are willing to put into making the right decisions or the lack of interest in changing automated actions (e.g., defaults) they do not consider important or are not even aware of. Techniques altering decision structure also include changing effort through friction modification (e.g., increasing elevator waiting time to promote staircase use) and manipulating the order of choices or using decoys (Stoffel et al., 2020).

The final cluster, 'decision assistance,' addresses the intention-behavior gap by reinforcing self-regulation. Techniques include reminders, such as text messages before medical appointments to boost vaccination rates (Milkman et al., 2021), and commitment facilitation, where, for example, pre-commitment to future retirement savings significantly increases savings rates (Thaler & Benartzi, 2004). This taxonomy facilitates the strategic development and implementation of multiple nudges, targeting specific psychological drivers or barriers for improved decision-making.

Figure 1

Taxonomy of choice architecture interventions (after Mertens et al., 2022)

Psychological barrier	Intervention category	Intervention technique
Limited access to decision-relevant information	Decision information: increase the availability, comprehensibility, and/or personal relevance of information	Translate information: adapt attributes to facilitate processing of already available information and/or shift decision maker's perspective Make information visible: provide access to relevant information Provide social reference point: provide social normative information to reduce situational ambiguity and behavioral uncertainty
Limited capacity to evaluate and compare choice options	Decision structure: alter the utility of choice options through their arrangement in the decision environment or the format of decision making	Change choice defaults: set no action default or prompt active choice to address behavioral inertia, loss aversion, and/or perceived endorsement Change option-related effort: adjust physical or financial effort to remove friction from desirable choice option Change range or composition of options: adapt categories or grouping of choice options to facilitate evaluation Change option consequences: adapt social consequences or microincentives to address present bias, bias in probability weighting, and/or loss aversion
Limited attention and self-control	Decision assistance: facilitate self-regulation	Provide reminders: increase the attentional salience of desirable behavior to overcome inattention due to information overload Facilitate commitment: encourage self or public commitment to counteract failures of self-control

Nudging and Choice Architecture in the Domain of Safety

Nudging applications in the domain of safety are limited in quantity as compared to other application areas such as health, economic decision-making and sustainability (see meta-analysis of Mertens et al. (2022) for an overview). The studies that do relate to safety are mainly situated in the domain of traffic safety (Avineri, 2014; Goldenbeld et al., 2016). An example of a successful safety nudge in the domain of traffic is the use of 'speed reduction markings' (National Academies of Sciences, Engineering, and Medicine, 2008), which are progressively narrower painted white lines that create a visual illusion of acceleration, prompting drivers to lower their speed (Thaler & Sunstein, 2008). Other examples are the use of personalized feedback to improve driving performance (Choudhary et al., 2019), or the use of salient seatbelt reminders (Lie et al., 2008).

While various common safety interventions in the process industry could classify as nudges, such as signalization or warning signals, very few to no studies have investigated the potential of nudge interventions for industrial safety as a distinct and complementary safety approach (Lindhout & Reniers, 2017). This is confirmed by a recent literature review of choice architecture applications in the construction industry (Sarpy et al., 2021) that found sparse nudge studies in the construction sector or related industrial sectors (e.g., farming and manufacturing). One study by Luria et al. (2008) found that visibility in the workplace moderated the level of manager-employee interaction after a supervisor coaching session, which in turn led to a greater compliance with ear protection. Another study by Rice et al. (2022), found that sending text messages could promote the number of performed toolbox talks (i.e., short safety talks) in construction. A last study by Zohar et al. (1980) in a steel plant, found that the use of direct feedback of temporary hearing loss, by showing hearing capacity graphs before and directly after shifts in noisy departments, was able to increase the compliance rate of wearing earplugs from 40% to 85%. The adoption of a nudge framework could both enhance the categorization of previous safety interventions that address the same psychological barriers, and stimulate the development of new safety interventions that complement and extend previous findings.

Lindhout and Reniers (2017) propose exploring nudging as a novel industrial safety tool, identifying improvement areas in industrial risk-taking. They distinguish between deliberate unsafe acts (e.g., considering rules unnecessary) and those stemming from automatic decision-making (e.g., memory lapses due to fatigue). In doing so, they take into account the role played by the management that enable unsafe choices (e.g., economic priority, poor instructions or lacking awareness). This approach aligns with safety models like the Swiss Cheese Model (Reason, 1990) and the Human Factor Analysis and Classification System (HFACS) (Shappell & Wiegmann, 2001; Wiegmann & Shappell, 2003), recognizing various causal layers for accidents (i.e., organizational, environmental, personal, etc.) and the role of intention in separating error from violation. This aligns with the fundament of the choice architecture taxonomy (Münscher et al., 2016) that built its clusters around trying to overcome the intention-behavior gap or to influence the intention for the better. It should be noted that nudges will not always be able resolve safety concerns stemming from flawed procedures or inaccurate instructions provided by team leaders. In general, nudges may aid in promoting better adherence to safety rules, given that the rules themselves are deemed appropriate.

CURRENT STUDY

The Belgian steel plant involved employs over 5000 employees and processes raw materials to steel coils and refined products via a chain of coordinated factories, including cokes plants, blast furnaces and sinter plant, hot- and cold rolling mills, galvanization lines and tailored blanks facilities. Although the safety standards at the industrial plant are rather high, a couple of thousands of incidents (i.e., near accidents) still do occur at their sites. These incidents align with the specific safety domains that typically account for the largest proportion of accidents (up to 75%) in the heavy industry, including working at height, handling heavy loads, contact with moving machine parts, gas hazards and traffic safety (Lindhout & Reniers, 2017). The current safety approach prioritizes technological innovation, upgraded Personal Protective Equipment (PPE), enhanced protocols and comprehensive employee training (e.g., handling unexpected crises). Advisors monitor safety and protocol compliance, and focused training targets influential employees to foster shared vigilance and enhance the safety culture. With the current interventions primarily targeting deliberate decision-making (system 2), there is recognition of the need for additional interventions addressing more automatic responses (system 1) and cognitive limitations to surpass the safety plateau.

We carry out two field experiments in this large steel plant to evaluate the effectiveness of nudge interventions as part of a holistic safety approach. We select two out of the five safety domains that typically account for the most safety accidents, including gas hazards and staircase safety (as part of working at height). The first aim of this study is to evaluate the effectiveness of nudge interventions in promoting gas detector compliance (RQ1), which is a crucial element in preventing gas hazards (Hall et al., 2021). The second aim is to investigate if nudges prove useful in mitigating unsafe behaviors involved in staircase safety (RQ2). Staircase safety is not only relevant in the process industry or for working at height, slips, trips and falls also account for one of the largest proportions of occupational accidents in general (European Agency for Safety and Health at Work, 2022).

EXPERIMENT 1

Gas hazards play a critical safety role in the process industry and the steel industry. These industries deal with various gases, some of which can be highly flammable, toxic, or explosive (Eckhoff, 2006; Linnerud et al., 1998). Gas hazards refer to any gas or vapor that can pose a risk to human health, safety, or the environment (Khan & Amyotte, 2002). The aim of the first experiment was to evaluate the effectiveness of nudge interventions in promoting gas detector compliance, therefore mitigating dangerous exposure to potential gas hazards.

Gas detectors are part of the critical personal protective equipment (PPE) in areas where gas is present. Yet, is it known that PPE compliance can be a hassle in the process industry for various reasons (e.g., workers considering the PPE unnecessary or impractical, the lack of clear guidelines and difficulties to monitor compliance on large industrial plants) (Man et al., 2021; Vukicevic et al., 2022). Although the danger of gas poisoning is a strong enough argument for many to respect precautionary measures, typically we see workers habituating to risks (Lee & Kim, 2022) and other behavioral drivers that lead to suboptimal gas detector compliance (i.e., memory lapses due to time pressure). The multinational steel producer involved in this study sees an incompliance of around 15% in the most recent years at their Belgian sites (as found by frequent tallying samples collected on a yearly basis).

We conduct a field experiment to measure the effect of two different nudges on safety behavior. The experiment takes place in a blast furnace and sinter plant of the industrial site, which is an environment that is exposed to gas hazards on a continuous basis. We focus one on of the most prevalent and dangerous gasses in this area, namely carbon monoxide (CO), which is a colorless, odorless, and tasteless gas (Ernst & Zibrak, 1998). The main components of gas detector compliance we aim at include wearing the gas detector, activating it and wearing it at the right place (i.e., on the left chest at breath height). The proper calibration of gas detectors is also important, but is not targeted in this study because it would entail more intrusive observation with high risk of confounding the study results by increased participant awareness.

Behavioral Techniques and Hypotheses

A round of informal interviews (n=10) two months before the start of the experiment reveal that most employees claim to be aware of the risk involved , but mainly forget to wear or activate the detector when they do not comply with the rules. In addition, they state that it is not always clear where the appropriate place for the detector is (e.g., on helmet, jacket or pants) and that it is not always clear where the more gas hazardous areas are. Therefore, our nudge interventions aim to assist in making safety choices, within Münscher et al. (2016) their cluster Decision Assistance. Relevant behavioral techniques and nudge concepts to promote gas detector compliance include reminders, priming, feedback, social norms and commitment.

First, cue-based reminders play a vital role in assisting individuals prone to forgetfulness amid daily distractions. Rogers and Milkman (2016) emphasize their superiority over written or electronic reminders, underscoring their underappreciation.

Second, the concept of priming, as explored by Bargh and Chartrand (2000), reveals how initial exposure to a stimulus can influence subsequent responses. Contextual changes, such as altering colors, can evoke distinct emotional and behavioral reactions, as highlighted by Tham et al. (2020).

Third, providing direct feedback can help to inform employees when they are not in order with their PPE's; similar to digital speed signs in traffic informing on the adequacy of speed (Gehlert et al., 2012). This relates to providing information for social comparison, which causes the greatest behavior change in the domain of climate change mitigation behaviors (d= 0.370), surpassing financial incentives (d= 0.317) (Bergquist et al., 2023).

Fourth, social comparison heavily relies on social norms, reflecting the substantial influence of others' actions and values (Bicchieri, 2017). This holds true in the workplace, where strategic use of social information can nudge employees towards better PPE compliance by displaying positive examples and limiting the visibility of non-compliance (Newaz et al., 2019).

Lastly, pre-commitment strategies, successful in pension saving programs like Save More Tomorrow (Thaler and Benartzi, 2004), assist individuals in adhering to their intentions. Workers in general state to be aware of the high risk of gas hazards and their willingness to comply. The emphasis here is on supporting workers in following through on intentions and strategically influence risk perception, that can diminish over time (Lee & Kim, 2022), to promote safety behavior (cf. 'Decision assistance').

Here, we will test the potential of a combination of the approaches above. The push buttons nudge intervention focuses on integrating commitment strategies and elements of (social) feedback, and is expected to have a positive effect on wearing, positioning and activating the detector (Hypothesis 1). This nudge includes a setup with a digital screen stating ‘CO detector activated and at chest height?’, accompanied with red and green push buttons (Figure 3). The screen also shows how many colleagues previously pushed the green button. The aim is to let people commit to a certain behavior, increasing the motivation to follow through with their intention, which can be amplified by seeing the good example of previous colleagues (i.e., social proof). Displaying information on the actions being adequate (green button) or dangerous and unaccepted (red button) provides clear feedback that assists in directing appropriate subsequent actions (i.e., activating and wearing detector correctly).

The second, icon nudge is a red triangle shaped icon placed at the jackets at chest height stating ‘CO detector here!’ with a little skull symbol on top (Figure 4). It serves as a visible reminder, including priming features to influence risk perception, and is expected to increase the number of people wearing gas detectors (Hypothesis 2a). The reminder is continuously active and visible when detectors are not worn correctly. When detectors are worn properly, the icon becomes invisible. This ensures the reminder's presence only when necessary, preventing the extinction of its effect. The approach aligns with shared vigilance for safety, allowing colleagues to easily identify non-compliance and serving as a reminder for them to address the issue as well. The use of a skull and red triangle is expected to prime negative affect (Kareklas & Muehling, 2014; Pravossoudovitch et al., 2014; Tham et al., 2020), inducing feelings of unsafety and anxiety, positively influencing the perceived risk (Slovic et al., 2005). We expect the effect to be similar on the various aspects of wearing the detector correctly, being wearing it at the right position and activating it (Hypothesis 2b).

The effect of both nudges is expected to be significant, but small (Hypothesis 3). Which in itself is not a problem, because of the high cost-efficiency of nudges and the difficulty of achieving any behavioral change for the safety domain at hand (any marginal increase is highly welcome).

Figure 3

Push buttons nudge

Figure 4

Icon nudge ('CO-detector here!')

Method

Participants

This experiment takes place in a blast furnace and sinter plant of the industrial plant, forming one joint department, where 85 blue-collar employees work. All internal workers are included in the experiment. These workers are all Dutch-speaking men. The average age is 33.08 years (SD= 10.85) and the average level of seniority is 10.26 years (SD= 9.53). The workers either worked in a rotating shift system (6h-14h, 14h-22h, 22h-6h, and a fourth shift was free of work), or in a day team (9h–17h). We set up two observation moments per week for each shift and the day team[2]. This way, there are eight observation moments per week and almost all 85 participants, except those that were in the 'free of work'-shift, were tallied weekly. For the number of observations, we are dependent on the goodwill and time of the line managers, the foremen and the participants, as well as time constraints. A power analysis conducted, using G*Power, assured that we would have more observations (n= 963) then needed (n=848) to find an expected odds ratio (OR) of 1.5, which is a small effect size (Sánchez-Meca, 2003). This aligns with the general conception in the literature that nudges commonly have a smaller effect size (DellaVigna & Linos, 2022). Before starting this study, approval is obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are free accessible for the employees on the intranet website of the steel plant. Ethical clearance for this study is provided by the safety department and labor unions of the industrial plant.

Research Design

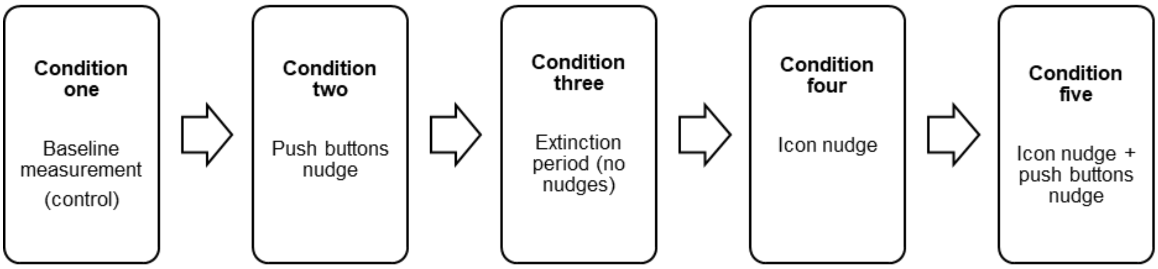
The first experiment has a within-subjects design (see Figure 2). All 85 participants are exposed to the same safety nudges in the same subsequent conditions. In the first condition, a baseline measurement of the safety behavior is performed, during which no safety nudges are implemented. In

[2] Collecting clustered data is difficult given the simultaneous presence of multiple teams and would require too intrusive observation methods to tell them apart (e.g., repeated questioning by observers or changing visible work wear per team). Therefore, the group of participants is treated as a homogenous group.

the second condition, the participants are exposed to the first safety nudge. In the third condition, this first nudge is removed during an extinction period. With this extinction period, we want to minimize the impact of the previous intervention on the next one. After this period, all participants are exposed to the second safety nudge in the fourth condition. In the last phase, the fifth condition, participants are exposed to both safety nudges at the same time. The order of conditions is the same for all participants, as the industrial plant only allows one intervention site, and work schedule and operational demands applied. Additional extinction periods were intended after the fourth ('Icon nudge') and the fifth condition ('Icon nudge + push buttons nudge'), but did not proceed due to unplannable operational demands and organizational constraints, so that a fully (counter-)balanced design was not possible.

Figure 2

Within-subjects design of nudge implementation (3 weeks per condition, except for the baseline measurement that lasted 6 weeks)



Materials and Procedure

Measures and Observation Method

Safety behavior in this experiment refers to the correct usage of the personal CO-detector by blue-collar workers at the blast furnace and sinter plant. This safety behavior consists of two actions. Firstly, the CO-detector has to be worn in the right place (on the left chest at breath height). Secondly, the CO-detector has to be activated. The dependent variables include 1) whether people carry the CO-detector (' Wearing detector'), 2) if the detector is activated ('Activating detector'), 3) the proper placement on the body ('Position detector') and 4) full compliance, which entails wearing the activated detector at the right place ('Correct usage). To investigate the safety behavior, on-site observations are organized in the workplace (i.e., where they should comply with the CO detector guidelines). Alternatives such as reading out data of the individual CO-detectors, using camera footage or self-reports are considered, but they are not included due to increased risk of socially desirable behavior, inaccurate measurements and/or privacy issues or adverse reactions. The on-site observations are conducted twice a week by foremen of each of the teams (the different shifts and the day team) using structured and standardized forms developed in collaboration with field experts (see Table A1 in Appendix 3A). Every observer receives a training, including a clear explanation of the objective, explanation of concepts on the observation form and practical guidelines to observe in a non-intrusive way. They are told that random double-checking can take place at any time to monitor tallying accuracy. The observers are instructed to observe between the start of the shift and the first subsequent break. The forms are filled out shortly after the observation, aiming to preserve the subtlety of the observations, and registered in Excel. The observers do not collect any personal data to ensure the anonymity of the workers. At the end of every month, both the anonymous observation forms and Excel files are sent to the researchers, allowing to control for data-entry errors. To limit potential confounding influences, the participants are told two months upfront that a general safety study would take place requiring data from multiple safety domains (incl. gas hazards), without further details. The temporal delay (i.e., 2 months), vague study description and clear instructions for subtle observations (e.g., strategic places, not standing still for too long, while talking, etc.), keep potential unwanted influences of in-person observations to a minimum.

Nudge Intervention Procedure

Push Buttons Nudge. The text on the display says "CO-detector activated and at chest height? --> Press the correct button!". The green button says 'yes', and the red button says 'no'. Also, an image of a worker with the correct placement of his activated CO-detector is shown. The display is placed at the exit of the shared cafeteria area, which all workers pass going back to work. Once they pass through this door, they should wear a CO detector, entering a potentially dangerous zone. It is here were observers check if they comply with safety rules or not (i.e., after interacting with the machine). Thus when leaving the cafeteria area, the workers have to push the button that indicates their behavior. When pressing green, the worker get this feedback message on a green screen: "Congratulations! You are well-protected!"; plus they see the real number of how many previous colleagues pushed the green button. When pushing red, the worker get this feedback message on a red screen: "You are in danger!"; the number of people pressing the red button is not displayed to prevent reversed social effects.

Icon Nudge. The icon nudge, a warning triangle plus text ("CO-detector here!"), is attached with hook-and-loop fasteners on the work wear of the workers at chest height. Attaching the icon with hook-and-loop fasteners on the outfits of all 85 participants, was done by a warehouse worker.

Both nudges are developed collaboratively with the safety experts. While the researchers propose innovative ideas using behavioral insights, based on informal interviews and observations, the safety experts monitor feasibility and fit with existing procedures. Labor unions are involved throughout the process, to evaluate the ethical appropriateness of the suggested nudges (cfr. FORGOOD ethical framework) and associated observation methods.

Data Analysis

To answer the hypotheses of the first experiment, multiple binary logistic regression analyses on the dichotomous variable counts are conducted. This type of analysis is suitable to examine the effect of multiple predictors (i.e., different experimental conditions) on binary variables (i.e., the correct usage of the CO-detector, tallied in different aspects). The logistic regression coefficients are used to calculate the OR which is an effect size measure that quantifies the association between two binary variables. It represents the odds of an event occurring in one group compared to another group. The OR is calculated by dividing the odds of the event occurring in one group by the odds of the event occurring in the other group. The OR can range from zero to infinity, with a value of one indicating no association between the two variables, a value above one indicating a positive association, as opposed values below one that represent a negative association. In general, the magnitude of an OR can be classified as small (1.5), medium (2.5), or large (4) (Chinn, 2000; Hasselblad & Hedges, 1995; Sánchez-Meca et al., 2003), although different fields and differences in the base-rate may imply different interpretations (Chen et al., 2010). Also, the Cohen's d is calculated to interpret the effect sizes (i.e., $d = 0.2$ small, $d = 0.5$ medium and $d = 0.8$ large). All analyses are performed in IBM SPSS Statistics for Windows, version 27 (IBM Corp., Armonk, N.Y., USA).

Results

During the 18 weeks of safety behavior observations, in total, we collected 1006 individual observations, of which 963 are included in the analyses. 43 observations are excluded since it was not clear if those data belong to internal workers or external contractors.

Push Button Nudge and Extinction

Based on the recorded data, we find out that in the push buttons nudge condition many workers pushed the buttons (2455 times on the green and 678 times on the red button, see details in Appendix 3B Table B1). This is a manipulation check to see whether workers actually do use the push buttons nudge. The aforementioned numbers show that this is the case. The results of the binary logistic regression analyses indicate that the push button interventions has a small significant effect on the wearing of the gas detector (OR 1.51, $p < .1$), but not on the other outcome variables (i.e., activating or position of the gas detector), when compared to the baseline condition (i.e., control without nudges). We do not find a significant increasing trend of the effect with the weeks passing by, which one could expect with the display of a continuously rising number of previously complying colleagues (cfr. social norms). When we take a closer look to the subsequent extinction period (i.e., removal of push buttons nudge); we see that the significant effect on the wearing of the detector disappears and that no significant effects are found on the other outcome variables. See Figure 5 for the compliance ratios in percentages by condition.

Icon Nudge

The results of the logistic regression analyses indicate that the icon nudge has a medium effect on the wearing of the detector (OR 2.21 $p < .01$) and activating it (OR 2.55, $p < .01$), compared to the baseline condition (i.e., control condition without nudges). On the other hand, it had a rather small effect on the position of the gas detector (OR 1.93, $p < .01$) and the completely correct usage (i.e., wearing at the right place and activated) (OR 1.71, $p < .05$). These results indicate that the workers are clearly more likely to wear the gas detector and activate the gas detector when the icon nudge is present (versus the absence of the nudge), but that they are only slightly encouraged to wear the protector at the right place; which ultimately reduces the nudge effect on full compliance.

Push Buttons and Icon combination

Besides evaluating the effect of the nudges individually, we also look at the combination of both nudges implemented simultaneously in a distinct experimental condition. Again, binary logistic regression analyses are conducted to evaluate the effect of the combined nudge condition on the binary outcome variables (i.e., wearing the gas detector, activating it and the right placement on the chest), compared to the control condition without nudges. The results indicate that the nudge combination have a large effect on the wearing of the gas detector (OR 5.02, $p < .01$), a medium to large effect on the activation of the detector (OR 3.34, $p < .01$) and a medium effect on both the right placement of the detector (OR 2.57, $p < .01$) and on being fully compliant (OR 2.77, $p < .01$). It appears that the combination of both the push button nudge and the icon nudge results in workers being significantly more compliant with the CO-detector guidelines, as compared to when they are working in the absence of those nudge interventions. The combination of nudges also seems to elicit a higher significant effect on full detector compliance (OR 2.71, p <.01) relative to the icon nudge (OR 1.71, p <.05) and the push buttons nudge (which is insignificant).

Table 1

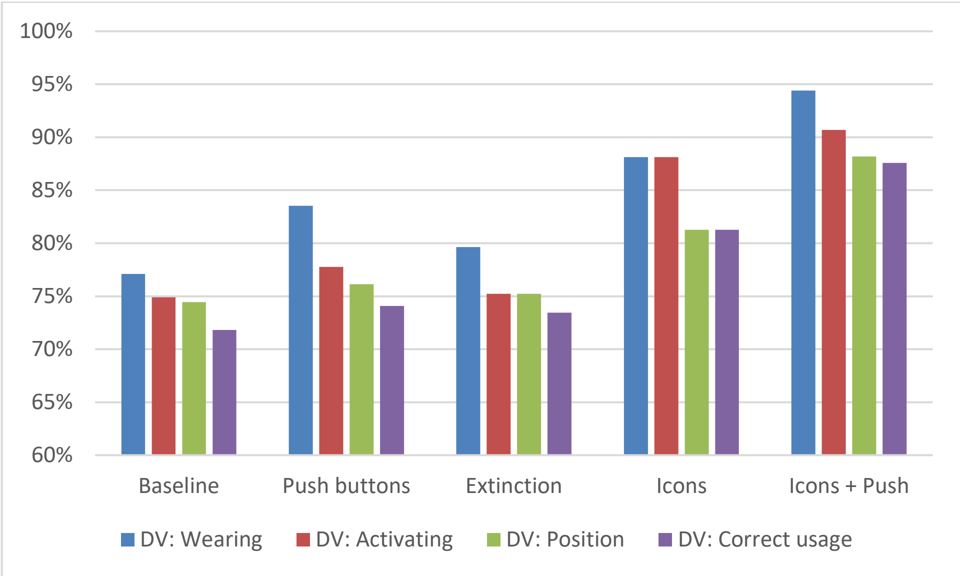
The effect of the nudges on gas detector compliance

VARIABLES	Wearing Detector		Activating Detector		Position Detector		Correct Usage	
	Exp (B)	*d*	Exp (B)	*d*	Exp (B)	*d*	Exp (B)	*d*
Push buttons	1.51*	*0.23*	1.20	*0.10*	1.10	*0.05*	1.10	*0.05*
	(1.754)		(0.846)		(0.423)		(0.452)	
Push buttons (extinction)	1.16	*0.08*	1.04	*0.02*	1.04	*0.02*	1.09	*0.05*
	(0.535)		(0.154)		(0.154)		(0.319)	
Icon	2.21***	*0.44*	2.55***	*0.52*	1.93***	*0.36*	1.71**	*0.29*
	(3.021)		(3.618)		(2.720)		(2.344)	
Icon - Push buttons	5.02***	*0.89*	3.34***	*0.67*	2.57***	*0.52*	2.77***	*0.56*
	(4.271)		(3.879)		(3.273)		(3.626)	
Observations	963		963		963		963	

Note. z-statistics in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control – Baseline measurement'.

Figure 5

The percentage of correct usage of the CO-detector among control and test conditions



Discussion

The first experiment examines the influence of two types of safety nudges, namely the push buttons nudge and the icon nudge on CO-detector compliance. The push buttons nudge has a small significant influence on the wearing of the detector, prompting individuals to get one, but not on activating or positioning. Those already wearing the detector may lack the reflex to check activation or correct positioning, while those not wearing it potentially forget to attend to it during routine walks to the lending machine. An activating reminder at the lending machine could mitigate this oversight. Adding extra information after pressing the red button (e.g., importance compliance and repetition guidelines) could also potentially increase the effect. The push button effect did not significantly increase over the weeks, as one could expect from a proportionate social norms effect of displayed numbers (Cialdini et al., 1999). Potentially, the rapid initial growth (up to 500 in 4 days) led to higher insensitivity to further increases, given that people think in relative sense (Bushong et al., 2020).

While we were able to monitor the use of the push buttons to some degree with push data (finding a regular pattern over three weeks), future replications could aim to observe the action with cameras or a badging system to account for every individual independently. Using cameras could clarify, for example, if people adjust the detector before pressing, press red and adjust after, or do not interact at all. Moreover, there is confusion in the factory's gas detector guidelines. Some supervisors and prevention experts permit wearing the gas detector on the helmet, provided it is at 'breath level,' contrary to the formal requirement of wearing it on the chest. This ambiguity may prompt individuals to relocate the detector to inappropriate positions, such as pants, shoulders or helmet, as noted by some workers post-experiment. This indicates the importance of clarity in prevention guidelines and the consistency in supervision (Newaz et al., 2019). No effects are found in the extinction period after removing the push button nudge, indicating both that the nudge effect disappears after removal as that the mere succession of in-person observations is not a determining condition for the establishment of the effect.

Overall, the icon nudge is more effective on all outcomes (i.e., activation and placement) than the push button nudge. It appears that a reminder that is omnipresent in the workplace, resulting in more nudge exposure, can be more effective. In addition, it is likely that a higher level of interactions with and visibility of this nudge amplifies social influence through shared vigilance (Brizon & Wybo, 2006), which results a bigger effect on gas detector compliance. Also, the danger-inducing icon (i.e., red triangle with skull) can contribute to a stronger corrective action via negative affect, as compared to the push button nudge that merely mentions ‘you are in danger!’ (Slovic et al., 2005). The priming effect of colors, including red as danger associations, is widely accepted (Pravossoudovitch et al., 2014; Tham et al., 2020), and increasing support is found for danger association of visual cues referring to death or dying (incl. skulls) to promote desired behavioral intentions (Kareklas & Muehling, 2014; Wogalter et al., 1995). Despite, our logical assumption between skulls and its relevance to gas hazard signaling should be further investigated. A tight time schedule did not allow us to pre-test the priming effect (i.e., comparing symbol with and without skull), but given the success of the intervention we advise to explore this in further research (e.g., online survey or lab study). The clear visual placement of the icon at chest height is assumed the reason for its significant effect on positioning, with the relatively smaller impact on position (compared to wearing) again being influenced by unclear prevention guidelines (i.e., breath vs. chest height).

The combination of both nudges has a medium to large effect on CO-detector compliance. This effect is larger than the nudges individually, which points at the additivity of nudge interventions. This finding aligns with previous studies in the nudge literature that show that often the effect of nudges interventions combined is larger than in isolation (Ayal et al., 2021; Brandon et al., 2019). This additivity is a promising answer to the critic of the rather small effect of nudge interventions as shown in recent meta-analyses (DellaVigna & Linos, 2022).

EXPERIMENT 2

Danger of falling from stairs is always present, especially in certain working environments and weather conditions. The cold-rolling pickling mill (CPM) at the industrial plant involved is a workplace dealing with a large amount of oil emulsion that coats surfaces, including the stairways, leading to a higher risk and number of falling incidents. When taking the stairs, both technical (e.g., the height of the steps, the handrail, the material of the stairs, etc.) and behavioral factors play an important role (e.g., holding handrails and adjusting speed). In a preliminary observation at the CPM, we saw that up to 25% of passersby did not hold the handrail when coming down the stairs. When asking a part of the group (n= 15) why they didn't hold the handrail, two months before the start of the experiment, they said it was for no particular reason; adding that it was presumably due to forgetting or by being in a hurry (cfr. economic time pressure). This is interesting in the light of 'nudgeability', as the lack of strong preferences often indicates a larger nudge potential (de Ridder et al., 2022).

Behavioral Techniques and Hypotheses

Some elements trying to increase the visibility of the footsteps for better foot placement (i.e., yellow markings footstep end; see Foster et al. (2014)) or to reduce the speed (i.e., gate at the top of the stairs) were already in place, so we focused on holding onto the handrail. The aim here is to create the intention and to remind people of the appropriate safety action, which apparently quickly escapes attention. Some behavioral techniques and concepts seem particularly interesting, including reminders, salience and priming.

Reminders can help to focus on staircase safety, when workers attention drifts due to daily work related tasks. This reminder needs to be salient, which can be defined as the characteristic of something that stands out from its environment and draws the individual's attention (Taylor & Thompson, 1982). Aiming to focus on S1 processing, the use of text will and should be limited or absent, considering that this involves more cognitive effort (cfr. S2 processing) (Kahneman, 2011). As workers indicate that they are indifferent to using the handrail or not, a simple reminder can be sufficient to make them use it. This reminder would also signal again the risks and dangers involved. Priming can be useful to prime unconscious thought preceding specific actions. Either by the use of color or by using other (visual) cues that influence the intended behavior. For example, Bargh et al. (1996) found that prior exposure to words associated with elderly stereotypes, led to participants walking slower towards the elevator upon leaving the laboratory.

The workers stated in their informal interviews that they are largely indifferent to holding the handrail or not, and most likely forget it or do not think about it when they do not use it. Therefore, it appears that trying to elicit an intention and provide assistance to follow through with this intention would be the right approach, tapping into Münscher et al.'s (2016) clusters Decision Information and Decision Assistance respectively. Following this rationale, a variety of nudges is developed to promote workers holding the handrails. The general concept is a hand print sticker that is placed on the handrail, which serves as a salient reminder attracting attention to handrail (Figure 6 and 7). The hand shape is meant to be an action cue that clearly indicates what action needs to be performed; being it through low effort conscious and potentially subconscious processing (i.e., hand shape activating subliminal relevant connections that stimulate the tendency to grab something). We believe that the use of reminders will significantly increase the number of people holding the handrail (Hypothesis 4), and in line with nudge literature, a small effect is expected (Hypothesis 5).

We choose to test the execution of the hand stickers in two colors, being blue and green. A first consideration is to have sufficient contrast on the yellow handrails and the fact that blue is a color often used for safety signage (e.g., required PPE's). Another consideration is the potential priming effect that green could have to accentuate the action as being good and desired. Red would have been relevant, as this is linked to increased negative affect and higher perceived risk, but it can be confusing in the way that it can indicate that people should 'not' grab the handrail (e.g., warning) or that it is forbidden. In addition, green spheres are tested to see if the hand shape of the intervention is determining for its effect; controlling for a mere salient colored cue that draws attention to the handrail being sufficient to install the effect. The effect of the reminder is expected to be different as the composition of the reminder changes (e.g., color and shape) (Hypothesis 6).

A relevant aspect of evaluating the effectiveness of the nudge includes dividing the desired behavior into two parts, being 1) holding the handrail and 2) holding the handrail for the full length. The latter is, logically, the safest option and the optimal outcome. We expect a significant increase in people holding the handrail at full length, but the effect is likely to be lower than the increase in people holding the handrail partially (as holding the handrail can be seen as a mild form of cumulating effort, which people tend to avoid) (Hypothesis 7).

Figure 6

Blue hand prints

Figure 7

Green hand prints

Method

Participants

This experiment takes place in a specific area of the CPM, with 3 dangerous staircases, where the internal workers (n=118) have to pass by multiple times during a shift. All internal workers were included. This group exists predominantly out of males (n= 115) with only 3 females working in these departments. The average age is 44.27 years (SD= 10.49) and the average seniority adds up to 18.42 years (SD= 12.66). The total of workers is almost equally divided over 4 teams, including team A (n=31), B (n=28), C (=30) and D (n=29)[3]. Per staircase a distinct part of the participants (i.e., equally distributed number, ranging between 37 and 39 individuals) uses one particular staircase, with limited use of the

[3] Team A (30 males 1 female; average age 47.45 (SD = 11.04); average seniority 18.16 (SD = 13.11)); B (27 males 1 female; average age 43.07 (SD = 10.47); average seniority 16.70 (SD = 13.04)); C (30 males female; average age 46.20 (SD = 10.25); average seniority 20.22 (SD = 12.18)); D (28 males 1 female; average age 41.49 (SD = 10.07); average seniority 19.38 (SD = 12.60))

other staircases throughout the shift. The demographics of these subgroups[4] are very similar to one another and is not expected to influence the results. A large number of observation is registered (n=2412) in order to include all teams on an equal basis for the control and experimental conditions[5]. Before starting this study, approval was obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are free accessible for the employees on the intranet website of the steel plant. Ethical clearance for this study is provided by the safety department and labor unions of the industrial plant.

Research Design

A mixed design is used, including multiple within-subject conditions per staircase, varying from control to experimental nudge conditions, and between-subjects comparisons between the staircases. Different experimental conditions are tested at staircase 2 (i.e., blue hands[6]) than at staircase 3 (i.e., green spheres and hands), while staircase 1 served mainly as a control location. In week 5 an experimental condition was introduced at staircase 1 (i.e., blue hand prints) to check if the effect would hold on another location too. The blue hands condition at staircase 1 was implemented one week earlier than instructed, due to unforeseen maintenance of nearby installations at week 6, and the camera at staircase 3 went out of service due to technical problems, complicating a fully balanced design. Table 2 shows an overview of the research design and sequence of conditions.

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[4] Staircase 1 (37 males 1 female; average age 43.93 (SD = 10.32); average seniority 17.51 (SD = 11.47)); Staircase 2 (39 males 1 female; average age 41.58 (SD = 10.44); average seniority 19.62 (SD = 10.75)); Staircase 3 (37 males 1 female; average age 48.12 (SD = 9.86); average seniority 22.15 (SD = 11.73))

[5] Collecting clustered data is difficult given the simultaneous presence of multiple teams and would require too intrusive observation methods to tell them apart (e.g., changing visible work wear per team). Therefore, the group of participants is treated as a homogenous group.

[6] We initially intended a 'blue spheres' condition preceding the first blue hands condition (staircase 2) to further disentangle the effects of symbol and color, but faced delay in delivery of the appropriate materials leading to a cancellation of this condition.

Table 2

Sequence of nudge implementations

	Week 1	Week 2	Week 3	Week 4	Week 5
Staircase 1	Control	Control	Control	Control	Blue hands
Staircase 2	Control	Blue hands	Blue hands	Blue hands	Blue hands (+)
Staircase 3	Control	Control	Green spheres	Green hands	/

Note: 'Blue hand (+)' indicates a higher number of blue hands on the handrail compared to 'Blue hands'

Materials and Procedure

Measures and Observation Method. The safety behavior included in this experiment involves holding onto the handrails, partially or for the entire length of the handrail. In addition, we controlled for the direction ('upward' vs. 'downward'), time of the day ('morning' 5:30-6:30 a.m., 'noon' 12:30-2:00 p.m. & 'evening' 9:30-10:30 p.m.), speed ('slow' vs. 'fast', by estimation) and passersby being in group or not (≥2). Camera footage is used to observe to what degree passersby comply with the handrail instructions for the three staircases. Two independent observers assess the footage. Every variable received a binary code, allowing a simple and direct data-input. Participants are informed two months upfront (to ensure forgetting) that a general safety study would take place requiring anonymous data-collection via camera-footage, without providing further details to limit confounding influences. Due to the time-consuming nature and the inability to observe multiple locations simultaneously without additional observers, in-person observations were deemed unsuitable.

Nudge Intervention Procedure

Following the sequence of the research design, polyester sphere and hand print stickers (i.e., green and blue) are placed at the handrails of the three staircases. The hand prints at the bottom of the handrail are directed upwards and at the top downwards (i.e., switching direction towards the middle) to align with the initial walking direction when approaching the stairs. We test the different effect of a lower (3 bottom and 3 top stickers per handrail, 12 for both sides) and higher number of hand prints stickers on the handrail (5 bottom and 5 top stickers per handrail, 20 for both sides). We choose for a minimum of three hands, top and bottom, to attract sufficient attention and install a base level of salience, and test a higher number of hands, with a maximum of 5 for the given length of handrail (avoiding overlap), to see if increased salience will benefit the impact.

Similar to the first experiment, the nudges are developed collaboratively with the safety experts following the same procedure. Again, labor unions are involved throughout the process, to evaluate the ethical appropriateness of the suggested nudges (cfr. FORGOOD ethical framework) and associated observation methods.

Data Analysis

Multiple binary logistic regression analyses are conducted to evaluate the effect of the nudge interventions, given the binary values of the dependent variables (e.g., holding the handrail or not). The OR is used to interpret the effect sizes, together with the Cohen's d. All analyses were performed in IBM SPSS Statistics for Windows, version 27 (IBM Corp., Armonk, N.Y., USA).

Results

During this experiment, 2412 observations are collected and no observations are excluded for analysis.

Nudge Interventions: Colored Hand Prints and Spheres

The results of the logistic regressions show us that the blue hand print stickers have a small to medium significant effect on both holding the handrail and holding it fully, with an OR of 2.32 ($p <$ .01) and 2.23 ($p < .01$) respectively, as compared to the baseline condition (i.e., control condition without nudges) (see Table 3). The higher number of blue hands also has a small to medium significant effect on both outcome variables with an OR of 2.71 for holding the handrail ($p < .01$) and an OR of

2.34 for holding it along the entire length ($p < .01$). The green spheres show no significant effect on either of the outcome variables. The green hand print stickers on the other hand show equally a small to medium significant effect on both holding the handrail (OR 2.37, $p < .01$) and holding it fully (OR 2.41, $p < .01$). When assessing the long-term effect of the blue hand stickers we still find the small to medium significant effect on holding the handrail, with an OR of 2.48 ($p < .01$), and on holding it across the entire length, with an OR of 2.10 ($p < .1$). See Figure 9 for the compliance ratios in percentages by condition.

Speed and Direction

Besides looking at the mere effect of the nudge interventions on the safety behaviors, also other covariates are taken into account, including the speed and the direction that people are going. The speed of people is an estimate of the observer and is divided into two categories being 'fast' and 'slow'. Little confusion exists as the distinction between being in a hurry or not is mostly clear. The results show that no significant effect was found here of people going fast, compared to people going slow, on holding the handrail or holding it completely. We do find a small significant effect of people going downward, which shows that they are 1.39 more likely to hold the handrail ($p <.01$), and 1.51 times more likely to hold it fully ($p <.01$), compared to people going upward (see Table 3).

Group Effects and Time of the Day

In addition, we are interested to see if people in group behave differently (i.e., a minimum of 2 persons or more) in comparison with individuals. We find a small significant effect showing that people in group were 1.25 times more likely to hold the handrail ($p <.1$), and 1.48 times to hold it fully ($p <.01$), relative to individuals (see Table 3). Lastly, we look for differences between different times of the day (i.e., morning, noon and evening). No significant effects are found here.

Organizational factors

In addition to the binary logistic regression analyses, another interesting finding originates from the observations. From the individuals that do not hold the handrail, up to 40% has their hands full with material. Leaving no free hands to hold the handrail. Some examples of the materials involved boxes and pipes, personal protective equipment's (PPEs), work toolboxes and backpacks.

Table 3

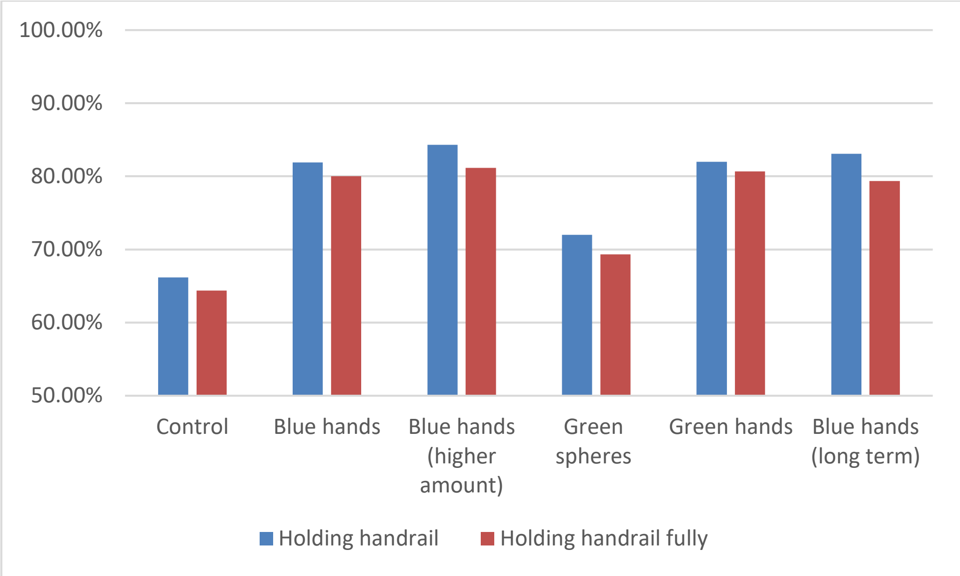
The effect of nudges and other covariates on handrail compliance

VARIABLES	Holding handrail		Holding handrail fully	
	Exp (B)	*d*	Exp (B)	*d*
Blue hands	2.32*** (-7.179)	*0.46*	2.23*** (-7.018)	*0.44*
Blue hands (higher number)	2.71*** (-4.72)	*0.55*	2.34*** (-4.293)	*0.47*
Green spheres	1.24 (-1.277)	*0.12*	1.23 (-1.079)	*0.11*
Green hands	2.37*** (-3.844)	*0.48*	2.41*** (-4.009)	*0.48*
Blue hands (long-term)	2.48*** (-4.413)	*0.50*	2.10*** (-3.829)	*0.41*
Speed (fast)	0.99 (-.081)	*-0.01*	0.87 (-1.077)	*-0.08*
Direction (downward)	1.39*** (-3.248)	*0.18*	1.51*** (-3.99)	*0.23*
Group	1.25* (-1.78)	*0.13*	1.48*** (-2.913)	*0.22*
Noon	1.05 (-0.393)	*0.02*	1.07 (-0.651)	*0.04*
Evening	1.13 (-0.969)	*0.07*	1.18 (-1.317)	*0.09*
Observations	2412		2412	

Note. z-statistics in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control', for speed 'Slow', for direction 'Upward', for group 'Not in group' and for time of the day 'Morning'.

Figure 9

The percentage of people holding the handrail among control and test conditions



Discussion

We aimed to evaluate the effectiveness of nudge interventions on the safety behavior of people using staircases. The findings suggest that nudge interventions (i.e., reminders), such as blue and green hand print stickers, can have a positive effect on people's safety behavior on staircases. It is noteworthy that the effects are relatively small, but still significant and very cost-effective (i.e., nudge cost around 20 euro per staircase). The lack of significant effects of green spheres may imply that the hand shape is a determining factor (cfr. action cue); more than the priming color of the implementation (i.e., blue or green) (Tham et al., 2020). Using the color red could have a bigger effect on risk perception (Luximon et al., 1998; Pravossoudovitch et al., 2014), but can be confusing to interpret the required action (i.e., 'holding handrail desired or forbidden?'). It should be noted that placing hand prints stickers on 'all' stairs could contribute to a more rapid habituation, diminishing the salience effect (Hall & Rodríguez, 2017). A strategical use of the nudges by placing them on the most dangerous stairs (e.g., higher and bigger staircases as opposed to very small ones) is recommended, depending on the context at hand.

The valuable findings related to other covariates highlight the importance of considering the direction of travel, speed and the social context in which people use staircases in promoting safety behavior. The bigger nudge effect on going downward, which is more dangerous, likely reflects an activation of risk related thoughts, being it deliberately (cfr. System 2) or more subconsciously (cfr. system 1). The group effects can be explained through social influence, leaning towards conformity (Asch, 1956; Cialdini & Goldstein, 2004) and herd behavior (Bikhchandani & Sharma, 2000; Le Bon, 1899). Here we see that it was not just the difference in pace that influenced holding the handrail in group, as the effect holds for people in group using the staircase independent of the space between the passersby on the staircases. The study's finding that up to 40% of people who did not hold the handrail had their hands full with material underscores the importance of considering organizational factors in promoting safety behavior on escalators. For instance, providing storage space and implementing policies that prevent people from using both hands to carry materials on stairs (e.g., elevators or two-person guideline), can increase the likelihood of people holding the handrail while using the stairs. This aligns with the HFACS model of Wiegmann and Shappell (2003) that stresses the different layers that contribute to safety behavior, going from organizational to individual factors.

Importantly, we see that the significant nudge effect of the blue hands hold over a period of three months, with a limited decline, which is crucial in evaluating nudging as a safety management tool. Those medium to long-term effect are less understood in nudging literature (Marchiori et al., 2017), making this is a promising result for (safety) applications 'in the wild' (Mazar & Soman, 2022). These insights can inform the development of interventions and policies aimed at promoting safety behavior on staircases, thereby reducing the risk of accidents and injuries, and their related costs (Chen et al., 2021; Gavious et al., 2009).

GENERAL DISCUSSION

Nudging has received a lot interest in the last decade, building on the work of multiple Nobel Laureates addressing the role of bounded rationality in human decision-making (Earl, 2018; Leahey, 2003). This vast amount of research is mainly concentrated in specific fields of research, including among others (behavioral) economics, health and well-being, and public policy (Dellavigna & Linos, 2022; Thaler & Sunstein, 2008). Little research is done in the domain of safety, except for traffic safety (Avineri, 2014; Goldenbeld et al., 2016), and almost no studies exist evaluating the nudge approach for industrial safety; despite its great potential (Kletz, 2001; Lindhout & Reniers, 2017). This study aimed to evaluate the potential of nudge interventions to promote industrial safety through two field experiments in the steel industry.

Evaluating Industrial Safety Nudges

This study forms a starting point for an ongoing structured evaluation of nudge interventions to foster industrial safety. Our two field experiments provide evidence that small cost-efficient nudges can promote safety behavior in the domains of gas hazards and staircase safety. Especially the nudges that were omnipresent at the workplace (i.e., the gas icon and hand shaped stickers), which resulted in a higher level of nudge exposure, seemed to be the most effective. This aligns with the complexity of safety behavior involving often not one, but repeated and endured necessary actions. Influencing single point decision, such as being an organ donor or not (Davidai et al., 2012), can sufficiently be influenced at one strategic point of time. Influencing endured desired behavior (e.g., constantly wearing gas detector) is likely to benefit more from a higher exposure to nudges throughout the day; which also increases the chance of eliciting positive social influence through shared vigilance (Brizon & Wybo, 2006). This in line with the system 1 and 2 reasoning, where system 1 benefits of assisting choice architecture at multiple relevant decision points, because of the lack of capacity of system 2 to keep this safe thought active during the day (Kahneman, 2011).

Interestingly, our findings confirm the previous finding in nudge literature that combined nudge interventions have a bigger effect than in those nudges in isolation (Ayal et al., 2021; Brandon et al., 2019). This additivity of our safety nudges is promising to counter the criticism on the smaller effects of nudges. If small, but cost-efficient, nudge effects can be combined for bigger impact, its relevance for safety management increases. This combination of nudges, either implemented simultaneously or in sequential fashion, holds the potential to foster a safety culture by making increased safety compliance more visible to other colleagues (e.g., altering perceived social norms, Bicchieri (2017)). In addition, making safety more visible and present through nudges could elicit the idea that managers put more effort into safety (DeJoy, 2005). This perception in turn might lead to reciprocal tendencies of workers (Molm et al., 2007), making them more willing to complftermy to safety guidelines (Walker & Hutton, 2006) and potentially more receptive to safety nudges. An important determining factor for nudges to support a change in safety culture is the long-term effect of those nudges. Our study finds some support of the persisting effects on the medium-long-term (i.e., 3 months) for the hand shaped reminders. The long-term effect of other safety nudges stills needs to be explored. This need holds not only for safety nudges, but also for nudge literature in general, which only provided limited results on lasting impact, underscoring the difference between specific types of nudges and the role of implementation context (Brandon et al., 2017; Marchiori et al., 2017; Van Rookhuijzen et al., 2021).

A New Psychological Framework for Addressing Industrial Safety Behavior

The fact that nudge applications exist in industrial safety practice and research, but have not been addressed as such, shows the lag of adopting the practice of nudging and dual-process theories of decision-making in this field. The benefit of this adoption would be to structure nudge development and to categorize existing interventions that enhances both communication of successful approaches and facilitates further improvement. By using this new psychological framework, more psychological depth can be provided in the evaluation of the human factors contributing to safety (Shappell &

Wiegmann, 2001). This can explain, and predict, workers experiencing high levels of fatigue or cognitive load (e.g., due to complex tasks or taxing working conditions) (Aldekhyl et al., 2018; Tinghög et al., 2016) to be less susceptible for system 2 interventions (e.g., safety campaigns, work instructions or training); for example due to memory lapses. Good choice architecture can help to structure workplaces (i.e., both physical and digital) that appeal to system 1 functioning, which keeps operational even during taxing work conditions (e.g., unexpected production problem, night shifts, extreme temperatures and environmental noise, etc.). The taxonomy proposed by Münscher et al. (2016) facilitates nudge development, relevant to the psychological barriers at play. The three clusters of nudge interventions defined provide a good starting point to develop industrial safety nudges and are likely to evolve along with the nudge literature. The new psychological framework discussed should not replace existing safety models, including those on safety culture (DeJoy, 2005; Vierendeels et al., 2018) or human factors (cfr. Reason's Swiss Cheese Model or HFACS), but should be treated as a complement that provides greater psychological depth.

Together with the new psychological framework of bounded rationality, and the associated practice of nudging, goes a necessary endeavor to rethink the ethical framework in which behavior change initiatives operate (Bowman, 2018). The FORGOOD framework can be used as a guideline to steer and evaluate the ethical application of nudges (Lades & Delaney, 2022), for both practitioners and ethical boards, but scholars agree that more rigorous monitoring practices (e.g., behavioral audits) and regulations are needed to control for unintended side effects of interventions or malicious attempts for manipulation (Chowdhurry, 2021; Mills, 2023). In addition, advancing machine learning technologies have made the proliferation of risk (e.g., misinformation campaigns) and the need for ethical protocols and risk mitigating actions more pressing (Mills et al., 2023).

Nudging as Part of a Holistic Safety Approach

The findings of the two field experiments show the potential of the nudge approach for industrial safety. The assessment of long-term effects and their scalability will need to enforce this statement in the near future (Lindhout & Reniers, 2017; Marchiori et al., 2017). This leads us to the question how nudge intervention can be integrated in a holistic safety approach that incorporates human, technical and organizational elements.

Both Reasons' Swiss Cheese model (Reason, 1990) and the HFACS model (Shappell & Wiegmann, 2001) highlight the multiple layers that contribute to unsafe behaviors, including organizational influences, (in)consistent supervision, preconditions for unsafe acts and unsafe acts themselves (discriminating between violations and errors). Taking the perspective of those models, the concept of 'layered nudging' can be introduced. Layered nudging captures the capability of nudge interventions to be implemented on multiple levels, being it vertical or horizontally. Vertical layered nudges are implemented at multiple levels in the (organizational) hierarchy, to prevent fallacies in decision-making processes that can contribute to safety accidents. This can be seen as an optimization of multiple lines of defense that prevent accidents to 'slip through the holes' of the Swiss Cheese metaphor. Horizontal layered nudging follows the same reasoning of lines of defense optimization, but focuses on multiple subsequent decision points that lead to a certain undesired action for a specific group or individual on the same hierarchical layer (e.g., relevant to gas detector compliance are picking up the detector, calibrate it, put it on correctly, etc.). Although the distinction between vertical and horizontal layered nudging can at times be useful, the main idea is that nudges can contribute to influence desired behavior by working on multiple levels (i.e., lines of defense), by optimizing managerial decision-making as well as influencing workers' unsafe behavior more directly.

Hallsworth (2023) proposes to use boundedly rational behavioral insights as a 'lens' to see human behavior and efforts to change it. By this, he means that technical improvements or alteration in the workplace, for example, should take into consideration their impact on the human element. Better-designed safety PPE's stored at a more inconvenient place could even be worse than the older models that were easily accessible because of a lower level of compliance. Those conflicts can arise from taking a more rational perspective, instead of this 'behavioral lens'. Hallsworth (2023) uses the term 'choice infrastructure' capturing the need of sufficient capability (and support) to use this behavioral lens from the very start, such as designing a new workplace, instead of trying to overcome existing problems by adding choice architectural interventions (i.e., nudges) when the new workplace appears to be misaligned with human behavior.

Limitations and Further Research

Methodological limitations of this study include having no separate control group in experiment 1, no consistent removal and re-entry of nudges to isolate the effect (e.g., ABAB), and similar nudges not being tested at multiple locations. Most of these limitations are due to limited resources and unforeseen practical challenges, common to field experiments (Samek, 2019), which on the other hand have the advantage of high ecological validity. They highlight the need to complement field studies with more controlled and affordable experiments (e.g., online or lab) and follow-up studies. Those follow-up studies should a) aim to replicate findings, b) zoom in on a specific nudges by testing a range slightly differing applications and c) test the same nudge at multiple locations (i.e., assessing both contextual moderators and scalability). Another way to meet these requirements is via collaborative action. Massive field experiments or 'mega studies' have been proposed as a novel and promising method to overcome common limitations in applied behavioral science (Milkman et al., 2021; Ruggeri et al., 2020). By collecting millions of data from multiple independent teams, these studies allow testing dozens of nudge variations in various contexts, and would enable a thorough assessment and optimization of future industrial safety nudges. These mega studies could equally provide more insights in how workplace conditions (i.e., individuals as employees, situational factors and cultural variations; Kubera (2023)) influence nudges differently than applications in public and private situations, by comparing the same nudges in those different settings.

Nudge effects often cumulate (Ayal et al., 2021; Brandon et al., 2019). Further research should explore why additivity of nudge effects seem apparent. Do combined nudges work on different psychological processes that add up, or is it just an increase of intensity of the same processes? Also, different types of nudges elements might influence certain individuals differently, as acknowledged by scholars who stress the need of for heterogeneity approach of nudging (Bryan et al., 2021; Hallsworth, 2023; Sunstein, 2022). This aligns with previous work highlighting the need to consider personality traits (i.e., agreeableness, conscientiousness, neuroticism) as key correlates of workplace safety (Beus et al., 2015). Future work should explore potential interactions between nudges and these personality traits to inform personalized behavior change interventions.

To evaluate industrial safety nudges effectively, a systematic analysis synthesizing relevant pre-existing safety interventions that qualify as nudges is crucial (Lindhout & Reniers, 2017). Münscher et al.'s (2016) nudge taxonomy provides a useful framework for this analysis, but continuous updates are necessary to accommodate ever new and harder to classify behavioral techniques (e.g., priming).

Some findings in this study show persistent medium-term effects of industrial safety nudges, but more research is needed to see if the effects endure for a longer period. Next to long-term durability, understanding contextual conditions that moderate or mediate safety nudges is equally essential, and aligns with the broader challenges the nudging approach faces today (Hallsworth, 2023). Consistently, exploring interactions between safety nudges and traditional interventions like informational campaigns and training (cfr. system 2) is a vital yet unexplored research direction. Positive findings regarding these interaction effects could validate the role of nudges in enhancing industrial safety management alongside more established interventions.

CONCLUSION

This study demonstrates that nudge interventions can be a promising approach to promote safety behavior in the process industry, particularly in the steel industry. The findings from the field experiments show that nudges, such as icons and hand print cues, were effective in increasing safety compliance among workers. This suggests that nudging can be a cost-effective solution to promote safety behavior and prevent severe accidents in the workplace. While nudging has been widely applied in different domains (including finance, health, traffic safety and sustainability), its relevance for safety in the process industry has not been systematically investigated. This study fills this gap by providing empirical evidence of the effectiveness of nudges in the steel industry. The organizational implications of a safety nudging approach are also discussed, highlighting the importance of integrating nudging into a holistic safety approach. In essence, the results of this study have important implications for the steel industry and other process industries, as they demonstrate the potential of nudging to improve safety behavior and prevent accidents. Further research could investigate the generalizability of these findings to other industries and explore the long-term effects of nudging interventions on safety behavior. Nonetheless, the present study provides a valuable contribution to the literature on safety interventions, emphasizing the importance of implementing a multi-faceted safety approach that includes nudging.

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CHAPTER 4

PROMOTING SAFETY TALKS WITH NUDGES: A LARGE LONGITUDINAL FIELD STUDY IN AN INDUSTRIAL PLANT[1]

Nudge interventions have been proposed as a new tool to promote industrial safety in the process industry. This study aims to evaluate the potential of nudges to promote the number and the distribution of safety talks. Two large field experiments (+300 000 observations) are performed at an industrial steel plant (+5000 employees) in Belgium, investigating the effect of reminders, social feedback and personal feedback. The results of the fist experiment show that all tested nudges have a small significant positive effect on the number of safety talks performed. The second experiment evaluates the long-term effectiveness of a feedback nudge over a very long period of 1.5 years. The nudge improved the spread of the safety talks, but the effect diminishes slightly over time. We conclude that strategic nudge development has the potential to become part of a holistic safety approach, yet further assessment of the long-term effects of nudge interventions and moderating contextual influences is needed.

Keywords: Nudging; Industrial Safety; Safety Talks; Process Industry; Decision-Making

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INTRODUCTION

Over the years, multiple approaches have been developed in industrial safety management to prevent serious accidents from occurring, ranging from technical improvements to better managing systems and the integration of the human factor analysis (Hudson, 2007; Reason, 2009). While constant technological and managerial innovations are needed, the importance of a deeper understanding of safety behavior became increasingly clear (Hopkins, 2006; Knegtering & Pasman, 2009). Research shows that up to 90% of occupational accidents are human-error related (Kletz, 2001). Unsurprisingly, experts agree that learning how to change safety behavior appropriately is one of the biggest remaining challenges.

Introducing the concept of safety culture in the last decades provided the field with insights in how social influence, driven by core values and beliefs, impacts safety behavior (DeJoy, 2005). Yet, the role of subconscious psychological drivers that influence safety decisions, and how to counter-act them, remains poorly understood. Nudge interventions have been proposed as an alternative method (Lindhout & Reniers, 2017) that complements classical safety approaches. Instead of targeting conscious and deliberate thought processes through instruction, protocols and training, these small behavioral interventions focus on making subtle changes in the decision context that interact with subconscious cognitive processes and their limitations (Thaler & Sunstein, 2008). The aim of this study is to build upon this proposition by evaluating the effect of safety nudges in promoting the number, and distribution, of performed safety talks on-site of a large Belgian steel plant (+5000 employees). The long-term effects of the safety nudges are monitored, in which we simultaneously address a gap in the nudging literature (Beshears & Kosowsky, 2020; Marchiori et al., 2017; Van Rookhuijzen et al., 2021).

The Importance of Safety Talks

Industrial safety is a crucial aspect of the process industry, and it requires the continuous implementation of safety protocols and measures. Safety talks or safety meetings encourage employees to remain aware of the potential hazards present in their working environment and the measures necessary to prevent accidents (Hinze et al., 2013; Zohar & Luria, 2003). A safety talk at an industrial site is a structured communication session, individual or in group, conducted by supervisors or safety professionals to promote safety awareness and reinforce safe work practices[2] (Kaskutas et al., 2016). Safety talks have proven to be effective tools in promoting industrial safety. Either by directly influencing safety awareness, risk perception and safety knowledge (Christian et al., 2009; Hoonakker et al., 2005; Huang et al., 2018; Sawacha et al., 1999), or by indirectly representing a good safety culture (Naji et al., 2022), known to have a big impact on safety behavior (Brondino et al., 2012; Kalteh et al., 2021; Vierendeels et al., 2018). Hinze et al. (2013) found that 'reported participation in safety meetings' in construction was one of the differentiating practices associated with a significant reduction in recordable injury rates. A 5-year longitudinal study of Hoonakker et al. (2005), found that regularly scheduled safety meetings were related to better safety results and lower safety insurance costs (often used as a safety outcome indicator). Lastly, a recent study of Naji et al. (2022) shows the mediating role that safety communication plays between safety culture and safety outcomes, further highlighting the importance of frequent safety talks.

Despite their importance, both the quality and the frequency of safety talks can be improved in practice. Olson et al. (2016) highlight multiple challenges, such as employee engagement, lack of personalization and a suboptimal frequency. Many employees consider safety talks to be a chore and consequently often pay little attention to the information presented. Organizations need to find ways to make safety talks more engaging and interactive (Forck, 2005). Another challenge is that safety talks are often not provided frequently enough (Arcury et al., 2012; Kines et al., 2010), which threatens

[2] A distinction can be made between safety meetings (i.e., more formal and longer talks with safety experts or supervisors discussing multiple hazards) and toolbox talks (i.e., shorter informal safety conversations before work or during breaks with direct supervisors and close colleagues) (Kaskutas et al., 2016). In this study, we focus on the more formal safety meetings, which will be further referred to as safety talks.

employee engagement keeping safety top of mind (Zohar & Luria, 2003). The Occupational Health and Safety Administration (OSHA) emphasizes the significance of periodic safety discussions, generally advising to perform one safety talk a month (contingent on the sector and company size; see OSHA (2016) and OR-OSHA (2019)). However, in case of the large multinational steel plant involved in this research, the predetermined goal of one safety talk per worker a month is often not met. In this study, we dig deeper into the psychological barriers that prevent supervisors to perform sufficient safety talks with the workforce.

The Boundedly Rational Individual

Over the last decades, research in human decision-making has shown that decisions and human behavior are frequently not the result of mere logical reasoning (cfr. Homo Economicus, see Persky (1995)). Simon (1997) argues that humans are 'boundedly rational', relying on subconscious simplified models and heuristics (i.e., mental shortcuts) instead of analyzing all the information available. Kahneman (2011) captures this metaphorically in his dual-process theory of decision-making (i.e., system 1 & 2). System 1 refers to the intuitive and automatic mode of thinking, which operates mainly without conscious thought. It operates effortlessly and quickly, relying on heuristics and immediate associations (e.g., linking a red color to aggression, see Tham et al. (2020)). System 2 represents the deliberate and analytical mode of thinking, is much slower and controlled, and requires conscious mental effort (e.g., complex mathematical calculations or safety education). Because our brain has little evolutionary interest or adaptation to operate in industrial plants, the mismatch between evolutionary heuristics and cognitive limitations, (cfr. system 1), and modern-day safety challenges (cfr. system 2), can partially explain the persistence of certain behavioral challenges and recurrent inadequate choices.

Nudging

The practice of nudging focuses on making subtle adaptions in the decision context – social, physical or informational – to steer behavior in the desired direction without limiting choice alternatives or economic incentives (Thaler & Sunstein, 2008). It aims to incorporate the contextual influences, by targeting system 1 more directly, and overcoming system 2 limitations (e.g., the inability to remember everything), when recreating the 'choice architecture' (i.e., the design and presentation of choice options) (Thaler et al., 2012). An example of a nudge is changing the defaults to promote organ donations, requiring an administrative action to opt-out instead of requiring an action to opt-in (Davidai et al., 2012). People tend to follow the path of the least resistance (i.e., inertia) and go with pre-set options when they are ignorant to the outcome, doubt which option is best or just don't care enough to spend energy on whatever action required (Michaelsen & Sunstein, 2023). Another example is the use of social comparison messaging to increase sustainable action. For instance , water and energy waste is reduced by providing information (e.g., e-mail or letter) about the actual use of resources by neighbors or other peers, providing a benchmark for one's own behavior. In a second-order meta-analysis, Bergquist et al. (2023) found social comparison to be even more effective ($d = 0.37$) than financial incentives ($d = 0.32$) to promote climate change mitigating behaviors. This effect occurs because people are heavily influenced by their social environment, including what others do and value (i.e., social norms, see Bicchieri (2017)).

Early discussions questioned the ethics of nudging, as some scholars deemed it manipulative (Lin et al., 2017). Nowadays, there is a consensus that nudging is accepted if the outcomes benefit both the practitioner and the target audience (e.g., improving health). In such cases, neglecting inappropriate choice architecture is unethical in itself (e.g., keeping unhealthy food at eye level at schools, which promotes consumption). Besides that consideration, it is also impossible 'not to influence': one has to determine the organ donation defaults to either 'yes' or 'no' anyway, and each of these has effects on outcomes (Sunstein, 2015). Importantly, nudges have proven to be cost-efficient (Benartzi et al., 2017) and to elicit mainly small to medium significant effects in a variety of applications domains, including health, finance and sustainability (Mertens et al., 2022). Recent debates questioned whether the nudge effect still holds when controlling for publication bias (Maier et al., 2022). A comprehensive study including data from governmental nudge units in both the UK and USA, that pre-register and report every experiment (i.e., less susceptible to publication bias) confirmed that the nudge effects 'in the wild' (8.7% increase over the average control) are smaller than in academic journals (33.4%), but that they still remain significant (DellaVigna & Linos, 2022). Because nudge effects are very context dependent (de Ridder et al., 2022), a heterogeneity approach, considering all moderating and mediating variables involved, is proclaimed by experts as the way forward (Bryan et al., 2021; Hallsworth, 2023; Sunstein, 2022).

Nudging Safety and Safety Talks

Nudge studies in the realm of safety, and by extension industrial safety, are still premature. Mainly traffic safety has known a surge in the last decades. One example includes the use of smart belt devices that provide an auditory reminder that becomes an annoying sound when the seatbelt is not buckled up (Lie et al., 2008). This reminding sound shows how nudges can assist the cognitive limitations of system 2. Limited cognitive capacity, or cognitive laziness, prevents people from remembering everything. A reminder helps the individual by directing the selective attentional process in the desired direction. In addition, a persisting sound becomes annoying, creating mental friction (i.e., cognitive resistance experienced when processing information, making decisions, or solving problems; see Dooley (2019)), which might motivate people to buckle up, because enduring the sound requires more cognitive effort than buckling up. Both nudge examples show how different small behavioral interventions can change human behavior by affecting system 1 more directly or by assisting the limited system 2 functioning.

Lindhout and Reniers (2017) propose the nudge approach as a new method to promote industrial safety in the process industry. They state that multiple safety interventions by definition fall under the criteria of a 'nudge' (e.g., painted arrows, signs and the use of colors), but that to this date little to no studies exist that investigate the effectiveness and strategic use of nudge interventions for industrial safety. We found one recent study of Rice et al. (2022) that nudges residential construction supervisors to increase the performance of regular on-site toolbox talks (i.e., short informal safety talks before work or during breaks) by sending short talk formats through text-messaging on the mobile phone; providing both inspiration for topics as serving as a mere reminder. The number of toolbox talks performed improved by 19% during the text message period. Interestingly, the term nudging is not mentioned in this study, although the tested intervention meets the 'nudge criteria', clearly showing the lag in adopting this framework for safety. The authors confirm that currently, no other studies have examined the potential of nudge interventions to promote the performed number of safety talks for occupational safety and that more research is needed to overcome their limitations (i.e., using a within-subject pre-post design with no control group and limited sample of 56 supervisors).

Performing safety talks can be seen as an outcome of a sequence of human decisions, and therefore, lend oneself to benefit from an optimized choice architecture (Thaler et al., 2012). People need to be informed about the specific number of talks that they need to perform, they need to remember at the given moment that they have to perform this talk and make it work with the rest of their schedule. Understanding the benefits of the safety talks, considering the amount of effort that is needed to register every talk and the influence of what colleagues do and value, are all factors that can influence the eventual decision of performing a safety talk (Olson et al., 2016). Considering all behavioral and contextual factors that influence the eventual action is needed to develop a tailored nudge intervention that promotes performing safety talks. In addition, one might wonder whether nudges should target behaviors that are indirectly related to an end goal (e.g., in this case promoting safety behavior and reducing accidents), or should instead only focus on the last person in the sequence performing the action. We argue that nudges should be used to counter inadequate decision-making on all levels, because accidents for example are a result of cumulated flaws in decision-making and suboptimal processes throughout the hierarchy of an organization (Wiegmann & Shappell, 2003). Recent studies show that nudging the behavior of regulators or other intermediates (e.g., customer service representatives) is a promising avenue to influence the behavior of end users, solving the problem at hand, complementing the narrow approach of solely targeting the last person in line (cfr. 'nudging the nudger', see House et al. (2022) and Dudley and Xie (2022). We conclude that nudges have the potential to improve industrial safety and that a holistic and strategic approach should be used to integrate nudges on multiple layers of the decision hierarchy leading to a given level of safety (cfr. 'layered nudging', see Costa et al. (2023)).

A Structured Approach: Taxonomy of Choice Architecture

By definition, nudges already exist in the field of industrial safety, but to this day, no overarching framework or strategy exists to implement them (Lindhout & Reniers, 2017). Münscher et al. (2016) propose a taxonomy to group nudging (or choice architectural) techniques in three separate clusters to strategize nudge development. Each cluster is built around a specific psychological barrier that the matching techniques try to overcome (for a comprehensive overview, see Mertens et al. (2022) and Münscher et al. (2016)). This taxonomy of choice architecture interventions can be used as a guideline to develop nudges in the field of industrial safety and beyond.

Decision information focuses on the limited access to decision-relevant information and tries to increase the availability, comprehensibility and personal relevance of information. Making information accessible and providing (direct) feedback are techniques that fall under this cluster and have proven to work in the field of sustainability. Cappa et al. (2020) showed that providing feedback on energy usage can reduce energy waste significantly. Likewise, by providing transparent information and feedback on how many safety talks are being performed, how those talks are spread over the workforce (i.e., aiming to reach as many employees as possible) and how other departments perform, could nudge practitioners to perform more talks and optimize the spread. The underlying mechanism entails the limitations of system 2 to keep track of everything and the limited access to decision-relevant information, which is countered by the nudge interventions at hand. Related to this is the use of personally relevant information (Mills, 2022b) and the use of social reference points to increase the impact of any message (Cialdini et al., 1999). Humans, as social beings, are heavily influenced by what other people do or value (i.e., by social norms, see Bicchieri (2017)). Displaying social information of exemplary behavior has found to be effective in promoting environmental conservation (Allcott, 2011; Goldstein et al., 2008), reducing bribery (Kobis et al., 2022) and increasing tax income (Torgler, 2004).

Decision structure aims to address the limited capacity to evaluate and compare choice options, and structures choice options by changing their arrangement in the decision environment or the format of decision-making. Changing defaults is a widely known technique that alters the decision structure by changing the standard setting from opting-in to opting-out, exploiting the tendency of humans to go with pre-set options that require no effort (i.e., cognitive inertia) (Michaelsen & Sunstein, 2023). They work when strong motivations for alternatives are absent, which may nevertheless concern fundamental life choices, for instance, increasing organ donation (Davidai et al., 2012) and pension savings significantly (Thaler & Benartzi, 2004). Reducing friction is a related technique that manipulates the mental or physical effort individuals have to do for a given action (Dooley, 2019). Vanhouten et al. (1981) found that increasing the closing time of elevator doors, implying a longer waiting time, increased staircase usage. By modifying friction that practitioners encounter when planning, performing and registering safety talks, one can expect a positive effect on compliance.

Decision assistance counters the limited attention and self-control of an individual by facilitating self-regulation. By providing reminders, one can overcome memory lapses and stimulate the desired action. A successful example is the use of text-based reminders to increase vaccine uptake (Milkman et al., 2021). Accordingly, providing sufficient reminders for scheduling and executing the planned safety talks would benefit the outcome, as confirmed by research from Rice et al. (2022), in which text reminders increased the number of toolbox talks in construction significantly (i.e., 19%). Another technique involves the use of pre-commitment strategies, nudging people to follow through with their intentions by exploiting the human tendency to reduce 'cognitive dissonance' (i.e., avoiding having conflicting beliefs and attitudes) (Festinger, 1957). Temporal landmarks, such as the beginning of the month, have been shown to amplify the impact of pre-commitment strategies (i.e., fresh start effect) for, among others, future savings (Dai et al., 2014).

Evaluating Nudge Effectiveness Over Time

The aim of any intervention targeting safety-related behavior is to achieve lasting behavior change. Safety culture approaches and behaviour-based safety programs, which focus mainly on operant condition[3] and system 2 interventions, including coaching (Geller, 2005; Nemeroff & Karoly, 1991), have proven to maintain positive effects over the long-term (Krause et al., 1999). The current nudging literature has a gap concerning long-term effects (Beshears & Kosowsky, 2020). The few studies that do exist show mixed results (Brandon et al., 2017; Marchiori et al., 2017; Van Rookhuijzen et al., 2021). The long-term effectiveness of nudges appears to be contingent upon the particular nudge types employed and the circumstances in which they are applied, highlighting the necessity for a comprehensive analysis of contextual variables that may influence their impact (Bryan et al., 2021; Hallsworth, 2023).

In a large-scale natural experiment with over 14 000 individuals, Gravert and Collentine (2021) found that descriptive social norms (i.e., providing information on what relevant others do, "72% of your neighbors are traveling with public transport occasionally") are not effective in nudging public transport usage. On the other hand, they found that economic incentives (i.e., a four-week free travel

[3] Operant conditioning is a learning process in which behaviors are shaped by their consequences, either through reinforcement or punishment (Nemeroff & Karoly, 1991). Reinforcing safe behaviors (e.g., wearing helmet) with (costly) rewards can enhance safety. However, when this reinforcement is no longer provided, extinction of the desired behavior can occur: the improved safety compliance is expected to gradually drop back to the baseline.

card) significantly increasing the uptake, which remained for months after removing the incentive pointing towards habit formation (i.e., automated actions largely driven by system 1). This study highlights both the importance of incorporating the heterogeneous effects of nudges (descriptive social norms do work in other contexts; see Bicchieri (2017) and Cialdini et al. (2006)), as the potential of behavioral interventions to foster habit formation after sustained exposure. The question remains what nudges are capable of maintaining their effect over time, which in turn could assist in developing adequate habits (Allcott & Rogers, 2014; Wood, 2019).

Lindhout and Reniers (2017) argue that nudges can be a useful contribution to industrial safety management to foster the current stagnating safety improvements. Therefore, a proper longitudinal analysis of safety nudging effects is necessary to push forward nudge theory as an established part of a holistic safety approach. Such a longitudinal analysis not only benefits the safety literature, but also entails an invaluable contribution to the scarce long-term evaluation of nudging in its entirety.

CURRENT STUDY

This study aims to investigate the effectiveness of nudge interventions in promoting the frequency (i.e., the number of talks) and spread (i.e., the number of employees that had a talk) of safety talks in the steel industry (RQ1), as well as examining the long-term maintenance of their effects (RQ2). Two field experiments are carried out at a Belgian site (+ 5000 employees) of a large multinational steel plant. The Belgian site processes raw materials to highly developed end products, through a variety of large separate departments (incl. blast furnaces, hot – and cold rolling mills, maintenance warehouse, raw material departments, galvanization lines etc.), allowing for an analysis of independent test and control groups. The Belgian steel plant aims to have at least one safety talk performed by every eligible supervisor a month (cfr. frequency) and for every worker to receive one talk each month (in line with standard OSHA guidelines, see OSHA (2016) and OR-OSHA (2019)). Given that both targets are consistently not met, a series of nudge interventions is tested to improve both the frequency and the spread of the safety talks among the workers in this firm.

In the first experiment, nudge interventions are developed to promote the number of safety talks performed. A series of interviews were carried out in various departments preceding the experiment to explore psychological barriers at play. Recurring themes are operational demands, making it challenging to allocate sufficient time for safety talks (i.e., setting other priorities) and forgetting to perform sufficient safety talks because of daily tasks taking up all the attention. Other barriers include the inconvenience of registering safety talks and the belief that some colleagues carry the team or, on the opposite, do not value performing qualitative safety talks in general. Various behavioral techniques are used to counter the psychological barriers at play, including reminders, reduced friction, social feedback and personal feedback. The reminder nudge (i.e., email format) assists in following through with the right intention by overcoming memory lapses and attention deficits (cfr. Decision Assistance), similar to the text reminder that proved effective in increasing the number of toolbox talks in construction (Rice et al., 2022). A safety talk registration link is added to this reminder to limit the required effort, minimizing the friction encountered in performing this action (cfr. Decision Structure) (Dooley, 2019). By providing feedback nudges, we address the limited capacity of individuals to access decision-relevant information (cfr. Decision Information), including personal and social information (cfr. social norms, Bicchieri (2017)), that has proven to work in previous studies (Cialdini, 2013; House et al., 2022; Zohar & Luria, 2003). In line with the nudging literature, we believe that the nudge interventions will have a small significant positive effect on the performed number of safety talks, including the reminder (Hypothesis 1), the social feedback nudge (Hypothesis 2) and the personal feedback nudge (Hypothesis 3). The personal feedback intervention is expected to have the biggest impact, as it acts most upon the performance of the individual directly (Hypothesis 4), while the reminder is expected to have the smallest influence (cfr. recent meta-analyses where Decision

Information generally outperforms the Decision Assistance cluster, see Mertens et al. (2022)) (Hypothesis 5).

The second field experiment examines how a nudge intervention can foster the spread of safety talks and whether this effect is maintained in the long-term. Safety results at the industrial plant show that the current spread averages around 40 to 50% of employees receiving no safety talks on a monthly basis. OSHA guidelines encourage regular safety talks with all workers (e.g., every worker receiving a talk once a month) (OR-OSHA, 2019; OSHA, 2016); this supports the consensus at the firm that the spread of safety talks among the employees should be improved. Psychological barriers are explored during the same interviews of the first experiment. The main barrier appears to be the lack of knowledge and transparency of the exact spread at a given moment in time. It is difficult to keep track of the spread without easily accessible mechanisms providing up-to-date information (other than personally analyzing the registered safety talks). Our cognitive capacity (cfr. system 2) simply does not allow us to remember this by heart in the case of large firms. Therefore, a feedback nudge is developed and tested providing information on the spread among the workers on a monthly basis. Similar to the feedback nudges in experiment 1, the focus here lies in providing accessibility to otherwise hidden decision-relevant information (cfr. Decision Information). A recent randomized control trial (RCT) showed that feedback nudges were capable of increasing the performance of service agents on increasing organ donation registrations (i.e., 25% increase) (House et al., 2022), further substantiating our choice for the intervention. The effect of the nudge intervention is monitored over a period of one year to investigate its sustainability. Hereby, we address both the gap in nudging literature concerning long-term effects (Marchiori et al., 2017; Van Rookhuijzen et al., 2021), as the robustness of the nudging approach as a newly established part of safety management (Lindhout & Reniers, 2017). We believe that the feedback nudge will have a small significant positive effect on the spread (Hypothesis 6) and that this effect will maintain one year later but decrease compared to the first month (Hypothesis 7).

EXPERIMENT 1

The effect of nudges promoting the number of safety talks performed is examined. A variety of nudge interventions is tested, including reminders, reduced friction, and personal and social feedback.

Method

Participants

The sample of the first field experiment consists of 1303 internal supervisors of the industrial plant (1241 men, M_{age} = 43.1, SD = 10.5) from 8 separate departments; including the Cokes Factory (COO, n= 69), Blast Furnaces (BF, n= 168), Raw Materials (RM, n= 127), Galvanization Line (GL, n= 108), the Cold-Rolling Pickling Mill (CPM, n= 199), General Services (GS, n= 154), Steel Factory (STL, n= 233) and Cold-Rolling Mill (CM, n= 245). A total number of 199 379 observations is collected. Before starting this study, approval is obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are freely accessible for the employees on the intranet website of the steel plant. Ethical clearance for this study is provided by the safety department of the industrial plant. All the registered safety talks are exported out of the registration software, allowing for non-intrusive data collection.

Research Design

A quasi-experimental pre-post design is used to evaluate the nudge effects per department, including five control departments with no interventions implemented (see Table 1). The reminder is tested at the COO, the social feedback nudge at CPM and the personal feedback nudge at the GL. Every condition lasts one month, except for the post-test that lasted 3 months to control for variations during the summer vacation period. The binary dependent variable is the blue-collar workers receiving a safety talk ('1') or not ('0') on a daily basis. The control departments include RM, BF, GS, STL and CM.

Table 1

Research design of the nudge implementation

Departments	Month 1	Month 2	Month 3-5
Cokes Factory (COO)	Baseline	Reminder	Post-test
Cold-Rolling Pickling Mill (CPM)	Baseline	Social feedback	Post-test
Galvanization Line (GL)	Baseline	Personal feedback	Post-test
Raw Materials (RM)	Baseline	Control	Post-test
Blast Furnaces (BF)	Baseline	Control	Post-test
General services (GS)	Baseline	Control	Post-test
Steel Factory (STL)	Baseline	Control	Post-test
Cold-Rolling Mill (CM)	Baseline	Control	Post-test

Procedure

Supervisors are expected to perform a minimum of one safety talk a month. This entails going to the workplace and discussing safety-related issues with one or multiple employees of choice (there are no strict duration guidelines). They can choose to indicate this moment in their Outlook agenda or perform this talk spontaneously when it suits them. To date there is no obligation in effect, because of irregular production requirements and the preference to safeguard employee autonomy.

The reminder at COO is sent via the Outlook mailing system twice a week (every Monday and Wednesday) containing the following message: 'Dear colleague, don't forget to schedule and register your safety talks. You can do this via the link below. Thank you very much!'. A hyperlink is added that leads directly to the page to register the talk, mitigating the effort to register (i.e., reducing friction).

The social feedback nudge at CPM involves a mail sent at the end of every week (again using Outlook). This mail consisted of two parts: 1) General information on the number of talks performed and what percentage this is from the monthly goal (this varies depending on the size of the departments) (i.e., 'This month we have set a target X safety talks. Up to now we have reached X safety talks, which is X % of our goal'). At the end of the first week, a progression of 25% is expected, in the second week 50% and so forth. 2) The second part contains information of how well all departments perform (with CPM generally being slightly under average in the last months, allowing to test upward social norm effects).

The personal feedback nudge is similar to the social feedback nudge; sent at every end of the week and consisting also out of two parts: 1) General information (identical to social feedback nudge) and 2) feedback on the personal progression ('You have reached X% of your goal').

Data Analysis

The hypotheses are examined using multiple binary logistic regression analyses on counts of the binary dependent variable (i.e., registered safety talks). Logistic regression coefficients are utilized to calculate the odds ratio (OR), which measures the association between two binary variables. The OR compares the odds of an event occurring in one group to the odds in another group. An OR of 1 indicates no association, values above 1 indicate a positive association, and values below 1 represent a negative association. The magnitude of an OR can be classified as small (1.5), medium (2.5), or large (4) (Chinn, 2000; Hasselblad & Hedges, 1995; Sánchez-Meca et al., 2003), although interpretations may vary across different fields and base-rate differences (Chen et al., 2010). Cohen's d was also calculated as an additional measure of effect size (0.2 = small, 0.5= medium, 0.8 = large). Separate within-subject analyses are carried out per department due to the difference in baselines among departments, which do not allow meaningful between-department comparisons (other than defining which department performs better in general). The statistical analyses were conducted using IBM SPSS Statistics version 27.

Results

The results of the binary logistic regression can be found in Table 2. The reminder nudge in the COO department has a small significant effect on the number of safety talks performed with an OR of 1.29 ($p < .01$, 95% CI: 1.11 - 1.50) when compared to the baseline (i.e., the baseline of the department at hand, one month before nudge implementation). The COO post-test (i.e., after nudge removal) shows a small to medium significant negative effect with a 0.55 odds ratio ($p < .01$, 95% CI: 0.48 – 0.63), indicating a significant decline of the performed number of safety talks compared to the baseline. The social feedback nudge at CPM has a small significant positive effect on safety talk performance with an odds ratio of 1.33 ($p < .01$, 95% CI: 1.18 - 1.51). The CPM post-test has a medium negative effect compared to the baseline with a 0.41 odds ratio ($p < .01$, 95% CI: 0.36 - 0.46). The personal feedback nudge at GL has an odds ratio of 1.57 ($p < .01$, 95% CI: 1.27 - 1.93), implying a small significant positive effect on performing safety that is slightly bigger than the other nudges. The GL post-test shows a small negative effect with an odds ratio of 0.74 ($p < .01$, 95% CI: 0.61 - 0.90), which aligns with the post-test of COO and CPM. The control departments show no positive effects of the control conditions compared to their individual baseline. The control condition of the BF has a non-significant odds ratio of 0.93 ($p > .1$ 95% CI: 0.82 - 1.05), similar to GS and CM having a non-significant odds ratio of 1.14 ($p > .1$, 95% CI: 0.96 - 1.36) and 1.05 ($p > .1$, 95% CI: 0.94 - 1.17) respectively. The control condition of both RM and STL have a small negative effect on the performed number of safety talks compared to the baseline with an odds ratio of 0.72 ($p < .01$, 95% CI: 0.63 - 0.84) and 0.84 ($p < .01$, 95% CI: 0.75 - 0.95) respectively. The post-tests of all control departments display a negative effect, ranging from small to medium (see Table 2 and Figure 1 for more information).

Table 2

The effect of the nudges on the number of performed safety talks

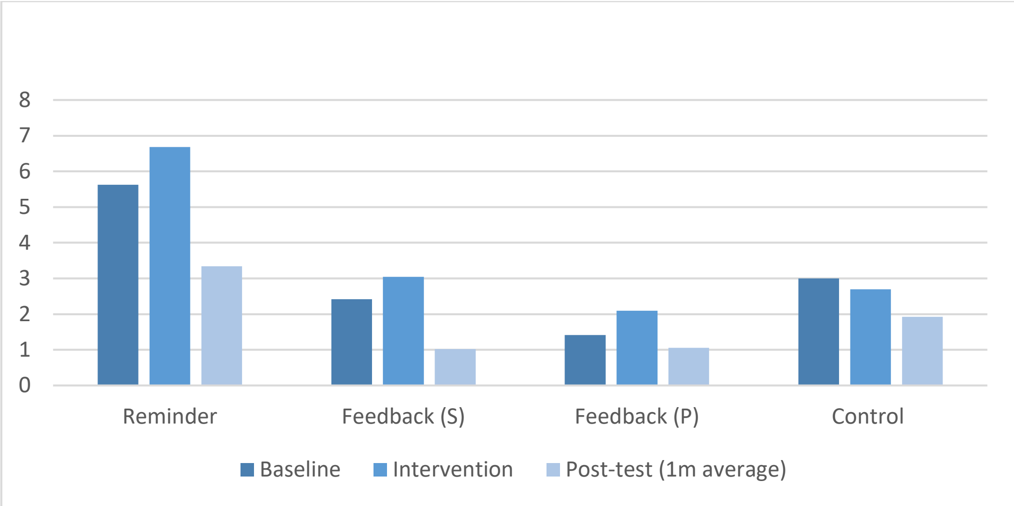
VARIABLES	Number of safety talks		
	Exp (B)	95% C.I.	*d*
COO			
Reminder	1.29***	1.11 - 1.50	*0.14*
Post-test	0.55***	0.48 - 0.63	*-0.33*
Observations	10 557		

CPM			
Social feedback	1.33***	1.18 - 1.51	*0.16*
Post-test	0.41***	0.36 - 0.46	*-0.49*
Observations	30 447		
GL			
Personal feedback	1.57***	1.27 - 1.93	*0.25*
Post-test	0.74***	0.61 - 0.90	*-0.17*
Observations	16 524		
BF			
Control (1)	0.93	0.82 - 1.05	*-0.04*
Post-test	0.66***	0.59 - 0.73	*-0.23*
Observations	25 704		
RM			
Control (2)	0.72***	0.63 - 0.84	*-0.18*
Post-test	0.51***	0.45 - 0.57	*-0.37*
Observations	19 431		
GS			
Control (3)	1.14	0.96 - 1.36	*0.07*
Post-test	0.49***	0.42 - 0.58	*-0.39*
Observations	23 562		
STL			
Control (4)	0.84***	0.75 - 0.95	*-0.10*
Post-test	0.64***	0.58 - 0.71	*-0.25*
Observations	35 649		
CM			
Control (5)	1.05	0.94 - 1.17	*0.03*
Post-test	0.71***	0.65 - 0.77	*-0.19*
Observations	37 485		

Note. *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Baseline'

Figure 1

The number of talks per person per condition



Discussion

We aimed to evaluate the effectiveness of nudge interventions promoting the number of performed safety talks. Both the reminder nudge (i.e., Decision Assistance) and the feedback nudges (i.e., Decision Information) appear to have a small significant effect on safety talk performance, with personal feedback eliciting a slightly larger effect. It appears that people benefit more from personal feedback on performance, providing insights into personal contributions and most likely, including feelings related to exposure, such as guilt or shame, than the comparison between other (better performing) departments that are too distant. This aligns with the proclaimed heterogeneity approach, advocating a tailored and personalized nudging strategy (Bryan et al., 2021; Mills, 2022b; Sunstein, 2022), with the personal feedback nudge having different personal effects on multiple target audiences (i.e., depending on your efforts). All control departments show no significant or very small significant negative effects, indicating the probable absence of uncontrolled external factors strongly enhancing the safety performance in that period. This confirms that the increase in the nudge conditions can be attributed to the interventions.

EXPERIMENT 2

In Experiment 2, the focus is not on the frequency of safety talks but on the spread of the safety talks among the workforce (i.e., rather than looking at the absolute number of safety talks in a department, here we try to maximize the number of different employees who have a safety talk within the department on a monthly basis). We examine the effect of a feedback nudge on the spread, and the maintenance of the nudge effect over time.

Method

Participants

The second field experiment contains a sample of 1380 internal supervisors (1317 men, M_{age} = 42.4, *SD* = 10.8) from 8 separate departments; involving the Steel Factory (STL, n= 233), General Services (GS, n= 154), Cokes Factory (COO, n= 69), Blast Furnaces (BF, n= 168), Raw Materials (RM, n= 127), Hot-Rolling Mill (HM) (n= 185) Cold-Rolling Mill (CM, n= 245) and the Cold-Rolling Pickling Mill (CPM, n= 199). A total number of 127 941 observations is collected. Similar to the first experiment, approval is obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are freely accessible to the employees on the intranet website of the steel plant. Ethical clearance for this study is provided by the safety department of the industrial plant. All the registered safety talks are exported out of the registration software, allowing for non-intrusive data collection.

Research Design

A longitudinal quasi-experimental design is used to evaluate the nudge effect on the spread of the safety talks at the SF department, including multiple independent control departments (i.e., GS, COO, BF, RM, HM, CM and CPM). The feedback intervention in this experiment can be automated in the short-term and therefore lends itself to a long-term analysis of the effect. Data on the spread are collected from March 2020 until November 2022. The intervention is implemented at the beginning of May 2021 and remains active onwards. The other departments are not exposed to any intervention influencing the spread and serve as a mere control.

Procedure

The feedback nudge in this experiment contains a mail that is sent at the end of every week via the Outlook mailing system since the first implementation of the nudge in May 2021. The message in the mail is the following: 'We aim to have every employee at the Steel Factory (STL) receiving at least one safety talk a month. Below you find a list of all your employees and the number of safety talks they received this month'.

Data Analysis

The impact of the feedback nudge (over time) is assessed through multiple binary logistic regression analyses, considering the binary nature of the dependent variables (e.g., receiving a safety talk or not). Effect sizes are interpreted using the odds ratio (OR) and Cohen's d. Again, separate within-subject analyses are carried out per department due to the difference in baselines between departments, not allowing for meaningful between-subject comparisons. IBM SPSS Statistics for Windows, version 27 (IBM Corp., Armonk, N.Y., USA) was employed to conduct all statistical analyses.

Results

The results of the binary logistic regression at STL are shown in Table 3. The feedback nudge at STL, in the first month (May 2021), has a large positive significant effect on the spread of the safety talks (i.e., maximizing the number of people receiving a talk on a monthly basis), when compared to the baseline (May 2020), with an odds ratio of 4.45 ($p < .01$, 95% CI: 3.50 - 5.67). Table 3 shows the evolution of the effect of both the control conditions (i.e., months without nudge prior to the nudge implementation) compared to the baseline (May 2021), as the changes of the feedback nudge over time (see Figure 2). The effect of the feedback nudge varies every month since its application, ranging from odds ratio of 2.28 to 4.97. In general, we see that the effect of the feedback nudge maintains as time progresses, but it slightly fades out. For clarity, Table 4 represents the average odds ratio of three periods (i.e., pre-intervention period 'Mar 2020 – Apr 2021', first-year intervention period 'May 2021 – May 2022' and the last 6 months period 'June 2022 – Nov 2022'). Here we see that at STL the average odds ratio for the control conditions during the pre-intervention period (Mar 2020 – Apr 2021) is 1.66, implying a small positive effect, 3.71 for the first-year intervention period (May 2021 – May 2022), which is a medium to large positive effect, and 2.74 for the last 6 months period, representing a medium positive effect when compared to the baseline (May 2021). The results of binary logistic regression for all control departments (incl. GS, COO, RM, BF, CPM, CM and HM) can be found in Appendix 4A (Tables A1 – A7). The average odds ratios in Table 4 show that most of the control departments display significantly smaller odds ratios for both the first-year of the intervention period 'May 21 – May 22' (ranging from 0.99 to 2.66) and the last 6 months period (ranging from 0.58 to 2.32). These effects are likely to be higher given a general appeal at the industrial site to perform more talks at the beginning of 2021 (i.e., increased monitoring and encouragement by middle management to meet the pre-set targets, explaining the drop at Jan 21 in Figure 2), whereas without, the difference between STL and the control departments would probably be greater. Only the control condition at the CM department reaches average odds ratios, in both these periods, above 2. However, given its high odds ratio in the period preceding the intervention 'Mar 20 – April 21' (i.e., 1.99), this can largely be explained by regression to the mean.

Table 3

The effect of the feedback nudge on the spread of safety talks (STL)

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	1.66***	1.36 - 2.07	*0.28*
Control (Apr 20)	1.73***	1.39 - 2.15	*0.30*
Control (June 20)	0.66***	0.53 - 0.83	*-0.23*
Control (July 20)	1.06	0.85 - 1.32	*0.03*
Control (Aug 20)	1.66***	1.36 - 2.07	*0.28*
Control (Sept 20)	1.25**	1.01 - 1.56	*0.12*
Control (Oct 20)	1.19	0.96 - 1.48	*0.10*
Control (Nov 20)	0.87	0.69 - 1.08	*-0.08*
Control (Dec 20)	0.77**	0.61 - 0.96	*-0.14*
Control (Jan 21)	1.27**	1.02 - 1.57	*0.13*
Control (Feb 21)	2.64***	2.10 - 3.30	*0.54*
Control (Mar 21)	3.69***	2.92 - 4.67	*0.72*
Control (Apr 21)	3.16***	2.51 - 3.98	*0.63*
Feedback spread (May 21)	4.45***	3.50 - 5.67	*0.82*
Feedback spread (June 21)	4.37***	3.44 - 5.56	*0.81*
Feedback spread (July 21)	3.21***	2.55 - 4.04	*0.64*
Feedback spread(Aug 21)	3.02***	2.40 - 3.80	*0.61*
Feedback spread (Sept 21)	3.14***	2.49 - 3.95	*0.63*
Feedback spread (Oct 21)	4.97***	3.89 - 6.36	*0.88*
Feedback spread (Nov 21)	3.31***	2.62 - 4.17	*0.66*
Feedback spread (Dec 21)	2.87***	2.29 - 3.60	*0.58*
Feedback spread (Jan 22)	4.41***	3.47 - 5.62	*0.82*
Feedback spread (Feb 22)	3.61***	2.85 - 4.56	*0.71*
Feedback spread (Mar 22)	3.63***	2.88 - 4.59	*0.71*
Feedback spread (Apr 22)	2.83***	2.25 - 3.55	*0.57*
Feedback spread (May 22)	4.37***	3.44 - 5.56	*0.81*
Feedback spread (June 22)	3.11***	2.47 - 3.92	*0.63*
Feedback spread (July 22)	2.41***	1.93 - 3.01	*0.49*
Feedback spread (Aug 22)	2.41***	1.93 - 3.01	*0.49*
Feedback spread (Sept 22)	3.18***	2.53 - 4.01	*0.64*
Feedback spread (Okt 22)	3.02***	2.40 - 3.80	*0.61*
Feedback spread (Nov 22)	2.28***	1.83 - 2.85	*0.45*
Observations	21417		

Note. *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control (May 20)'

Figure 2

The evolution of the spread of safety talks over time (vertical line representing nudge implementation and 'Control' the average of control departments)

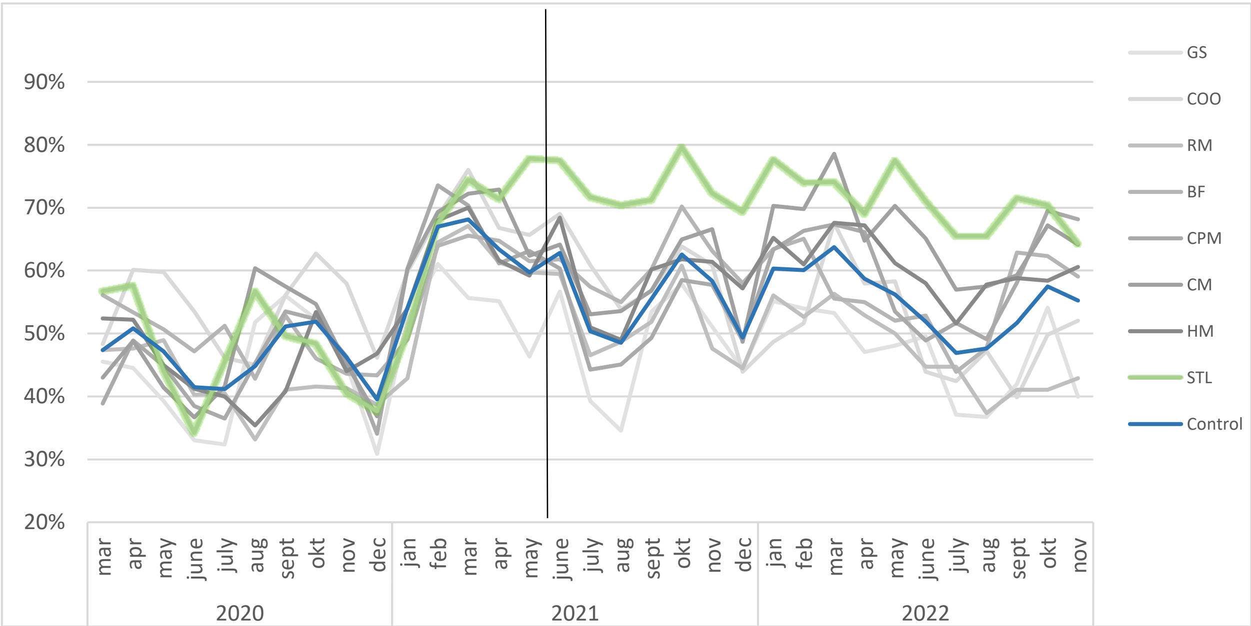


Table 4

The average odds ratios for each department in three distinct periods

	STL (Feedback)	GS (C)	COO (C)	RM (C)	BF (C)	CPM (C)	CM (C)	HM (C)	Control Avg.
Mar 20 – Apr 21	**1.66**	1.48	1.00	1.01	1.13	1.46	1.91	1.40	**1.25**
May 21 – May 22	**3.71**	1.55	0.99	1.20	1.49	1.74	2.66	1.96	**1.66**
June 22 – Nov 22	**2.74**	1.22	0.58	0.76	1.23	1.80	2.32	1.67	**1.37**

Note. 'C' stands for 'Control condition' and 'Control Avg.' refers to the average of the odds ratios of all control departments for a given period.

Discussion

We evaluated the effect of a safety nudge improving the spread of the safety talks and the maintenance of the effect over time (i.e., 1.5 years). The results show that the feedback nudge has a large significant positive effect on the spread of safety talks in the first month, meaning that a higher number of different individual employees have a safety talk in the department with the experimental manipulation in comparison to the control departments. The effect maintains over time, but knows a decline, ending with still a medium to large effect in the last months, after a long period of 1.5 years. This illustrates the possible sustainability of nudging effects. Most of the control departments know a small significant positive effect during the same intervention period, implying a general trend towards better spread. However, the effect in the other departments is significantly smaller than at the STL (incl. feedback nudge), showing that external factors cannot account for the medium to large nudging effect. Of course, in field experiments, especially in complex industrial settings, control of all variables affecting behavior is impossible. On the other hand, the ecological validity of an actual factory ensures the real-world applicability of behavioral interventions (Beshears & Kosowsky, 2020), and their significant effect above all possible natural, simultaneous contextual variation. It is also important to note that our huge sample size constitutes the necessary noise buffer to detect the intervention effects (Harrison & List, 2004). We conclude that the feedback nudge intervention worked, providing access to covert information (cfr. cluster Decision Information) and up-to-date information on the supervisor's efforts; and that the effect maintains for at least 1.5 years, be it with a declining effect size. Further evaluation is needed to see whether the effect stabilizes or fades out over time.

GENERAL DISCUSSION

Nudging has garnered substantial attention over the past decade, drawing on the contributions of esteemed Nobel Laureates who have examined the impact of bounded rationality on human decision-making (Earl, 2018; Leahey, 2003). While a wealth of research has been conducted in specific fields such as (behavioral) economics, health and well-being, and public policy, there has been limited exploration of nudging within the realm of safety, with the exception of traffic safety (Avineri, 2014; Goldenbeld et al., 2016). Surprisingly, few studies have evaluated the application of the nudge approach in industrial safety despite its great potential (Kletz, 2001; Lindhout & Reniers, 2017). This study aimed to evaluate the role nudges can play in fostering the number and spread of safety talks performed at a steel plant and the maintenance of the effect over time.

Nudging the Frequency and Spread of Safety Talks

Our findings demonstrate the effectiveness of nudging to influence safety communication practices in the workplace. Experiment 1 demonstrated the varying effects of different nudges on safety talk frequency within departments. The reminder nudge implemented in the COO department resulted in a small significant increase in safety talks, while the social feedback nudge in the CPM department also showed a small positive impact. Providing social information of more closely related peers (e.g., teams instead of departments) might have exerted a stronger influence, either upwards or downwards, depending on peer performance (Cialdini et al., 2006; Goldstein et al., 2008). In contrast, the personal feedback nudge at GL demonstrated a slightly stronger effect. These findings align with previous literature highlighting the potential of nudging to influence behavior change in specific contexts when integrating more personalized nudge interventions (Milkman et al., 2021; Mills, 2022b). Together with the study of Rice et al. (2022), successfully nudging toolbox talks with text reminders, these findings highlight the potential of nudges to promote the frequency of safety talk performance. Interestingly, the post-tests conducted after the removal of the nudges showed a decline in safety talk performance compared to the baselines. This finding suggests that the presence of nudges played a crucial role in sustaining the desired behavior change. It implies that an ongoing or extended presence of the nudges is necessary to maintain the positive effects of nudging interventions (Bernedo et al., 2014). Experiment

2 focused on supervisors spreading their safety talks more evenly among the workforce and examined the effects of a feedback nudge. The results demonstrated that the feedback nudge had a significant positive impact on increasing the number of workers receiving at least one safety talk every month. In line with House et al. (2022), feedback nudges prove to be a useful nudging technique to enhance (supervisory) decision-making, extending further than merely influencing the safety behavior of workers (cfr. 'nudging the nudger', see also Dudley and Xie (2022)). The findings suggest that nudging can serve as a valuable tool in promoting the frequency and spread of safety talks, encouraging employees to engage in meaningful discussions about safety-related issues (Zohar & Luria, 2003).

Long-Term Nudge Effectiveness and Habit Formation

While the short-term effects of nudging interventions have been explored extensively, the long-term effectiveness of nudges remains an area of ongoing research (Marchiori et al., 2017). Long-term effects of nudges may be contingent upon various factors, including the specific types of nudges employed and contextual variables (Brandon et al., 2017; Congiu & Moscati, 2022). Therefore, conducting comprehensive longitudinal analyses of safety nudging effects is essential for establishing nudges as an integral component of safety management (Lindhout & Reniers, 2017), next to the already proven behavioral-safety and safety culture approaches (Geller, 2005; Krause et al., 1999). The feedback nudge in experiment 2 displayed a positive significant effect on the spread of safety talks. However, the effect diminished over time, going from a large to still a medium positive effect after a very long period of 1.5 years. Further evaluation is needed to see if the effect stabilizes or keeps diminishing, indicating the need for continued monitoring and adaptation of nudging interventions to ensure their long-term effectiveness (Beshears & Kosowsky, 2020). While nudge interventions primarily aim to address system 1 processes, Banerjee and John (2021) argue that some elements of reflection (e.g., self-awareness and internal reflection) are likely to make nudges more effective and promote its long-term maintenance (referred to by them as 'nudge plus'). Given that our interventions (i.e., reminder and feedback) tend to be conceived more consciously than other nudging techniques (e.g., priming mood through colors, see Tham et al. (2020); this can have contributed to the long-term effectiveness of the nudges.

Relevant to long-term nudge effects is the aspect of habit formation. Habit formation is a process by which behaviors become automatic responses to specific cues or contexts and is a critical factor in promoting lasting behavior change (Wood & Rünger, 2016). The findings of the first experiment show that a short nudge implementation of 1 month does not show any learning effect or habit formation, as the effect does not hold. Previous research has shown that nudges were able to maintain a certain effect after the nudge removal by influencing habit formation (Allcott & Rogers, 2014; Bernedo et al., 2014; Vanhouten et al., 1981). Making behaviors habitual depends on various factors (incl. context, rewards and repetitions; see Wood (2019)) that are targeted by nudging. Nudging influences both the context and the number of repetitions, meaning that understanding the dynamic (and interaction) between endured nudge effectiveness and habit formation will be crucial to evaluating long-term nudge effectiveness. Here, the feedback nudge remained active in the second experiment, not allowing us to evaluate potential habit formation. Note that for the spread of safety talks the access to decision-relevant information is pivotal, which might hamper the performance of habits in its absence.

Strategic Development of Nudges as Part of a Comprehensive Safety Approach

Nudging techniques offer a promising approach to behavior change in the realm of industrial safety. To guide the strategic development of effective nudges, Münscher et al. (2016) proposed a taxonomy that groups nudging techniques into three clusters. This framework provides valuable guidance for leveraging nudges as part of a comprehensive safety approach.

Three clusters are discussed, including decision information (i.e., altering the access, the content or comprehensibility of decision-relevant information), decision structure (i.e., altering the format or arrangement of choice options) and decision assistance (i.e., helping to follow through with intentions with reminders and pre-commitment) (see Mertens et al. (2022) for the related effect sizes). Important psychological barriers preventing sufficient and dispersed safety talks appeared to be the limited access to (personally) relevant decision information, administrational efforts, reliance on well-performing colleagues and memory lapses due to competing daily operational tasks. Defining the psychological antecedents helps to develop nudges that can counter those barriers (Hallsworth, 2023). Feedback nudges were used to promote accessibility of information and making it more personally relevant (cfr. Decision Information) and reminders, including hyperlinks to registration forms, assist in overcoming memory lapses and to reduce friction (i.e., the required effort) (cfr. Decision Assistance and Decision Structure). The psychological barriers at play show how the limited capacity of system 2 can hamper decision-making and how managing the safety efforts can benefit from small adaptations in the choice architecture.

Nudge interventions in itself are not entirely new to the realm of safety. Signs, the use of colors, arrows and so forth, have been around for hundreds of years (Lindhout & Reniers, 2017). The novelty is in its strategical development and understanding of the mechanisms underlying their effectiveness, for instance through the dual-process theory of decision-making (i.e., system 1 and 2) (Kahneman, 2011). The strategic development of nudges within the framework proposed by Münscher et al. (2016) holds promise for enhancing safety practices in industrial settings. By aligning nudges with the taxonomy clusters and considering their role in decision information, decision structure, and decision assistance, organizations can address psychological barriers and leverage behavior change principles to promote a safer work environment.

Limitations and Further Research

Despite the valuable insights gained from our study on nudging the frequency and spread of safety talks among workers, several limitations should be acknowledged. These limitations open avenues for further research, highlighting important aspects that warrant exploration in the field of nudging and safety interventions.

Our study primarily focused on implementing nudging interventions in real-world settings through field experiments (cfr. 'behavioral science in the wild', see Mazar and Soman (2022)). While this approach offers valuable insights into the practical application of nudging techniques, further research (e.g., online vignette study) is needed to compare more variations of the tested nudges to assess their effectiveness, including different text formats of reminders or feedback messages, the frequency of the messages (i.e., daily, weekly, monthly) and messenger effects (i.e., who provides the reminders or feedback, see Hafner et al. (2019). In real life, this requires scarce resources, while online experiments with vignettes might be able to test a great number of conditions in an efficient way. The ones that prove to be the most effective can again be tested in practice with a higher ecological validity. In this study, we faced some organizational constraints (i.e., limited resources and IT capacity for automation) that prevented to evaluate the long-term effectiveness of the nudges in the first experiment. Technological innovations (or advanced technological firms) would allow to automate the provision of feedback (incl. multiple variations) and easily monitor its long-term effects. Current advances in artificial intelligence (AI) even allow going further by creating algorithms that could optimize the feedback format automatically (e.g., updating every month with variations among departments) depending on the related outcomes (cfr. 'hypernudging', see Mills (2022a) and Mills et al. (2023)), and should be explored in the field of industrial safety too.

The examination of how nudging relates to and complements other programs and communication strategies is another crucial element. Understanding the synergies and potential conflicts between nudging interventions and more typical system 2 interventions (incl. coaching and training) can inform the development of comprehensive safety approaches. In this study, we nudged supervisors to perform more talks instead of providing the supervisors workshops or presentations (i.e., conventional system 2 intervention) that highlight the benefits of safety talks. Safety talks align with a more typical system 2 approach, so here we used nudges to optimize the performance of a typical system 2 intervention that has proven to have a significant positive effect on safety-related conduct (Hoonakker et al., 2005; Olson et al., 2016; Rice et al., 2022). How effective nudging successful system 2 interventions is compared to nudges that directly influence worker safety behavior (e.g., signs or sounds), or the combination of both (cfr. layered nudging, see Costa et al. (2023)), still has to be investigated.

In addition, research on the long-term effectiveness of nudges and their contextual influences will contribute to advancing the application of nudges as an integral part of comprehensive safety management. Our results on successful long-term nudge applications are among the few (Marchiori et al., 2017; Van Rookhuijzen et al., 2021). Behavioral interventions that remain effective for an extended period of time have also proven to contribute to habit formation (Bernedo et al., 2014; Brandon et al., 2017). Further research will need to indicate if safety nudges (e.g., feedback nudge promoting the spread of safety talks) are capable of forming sustained safety habits and under which conditions (i.e., necessary effect size, repetition and duration of intervention) (Gravert & Collentine, 2021; Wood, 2019). In line with the foregoing, how long the effect of a safety talk lasts on safety behavior and how this translates to long-term safety results remains poorly understood and should be explored further (Hoonakker et al., 2005; Rice et al., 2022).

CONCLUSION

Nudging has gained attention as a behavior change approach, yet its application in safety, particularly in industrial settings, remains limited (Lindhout & Reniers, 2017). Our study evaluates the effectiveness of nudging in promoting the number and distribution of performed safety talks at a steel plant. The results highlight the potential of nudging to influence safety communication practices, with reminders, social feedback, and personal feedback nudges showing significant positive impacts. The large positive influence of a feedback nudge on the spread of safety talks persisted after 1.5 years, although the effect faded out slightly over time. The strategic development of nudges, guided by the proposed taxonomy of choice architecture (Münscher et al., 2016), offers promise for enhancing safety practices. However, further research needs to explore the long-term effects of other nudging techniques and their interaction with currently established safety approaches.

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CHAPTER 5

PREVENTING HAZARDOUS EXPOSURE TO SUSPENDED LOADS WITH NUDGE INTERVENTIONS[1]

This study investigates the effectiveness of nudging strategies in enhancing safety practices related to suspended loads in industrial settings. Three field experiments featuring social proof, friction and salience nudges revealed that all interventions effectively increased the distance to suspended loads, promoting safer practices among workers. The social proof experiment found displaying the number of colleagues following safe pathways increases its usage. The friction experiment found the nearby placement of no-touch tools to be more effective than supervisory communication. In the salience experiment, a light projection beneath suspended loads is found to significantly promote keeping distance. These effects persisted over an extended period, signifying long-term safety potential. A layered nudging approach, combining horizontal and vertical strategies, emerged as a key recommendation. Horizontal nudging aims to mitigate risks through multiple simultaneous nudges, while vertical nudging amplifies the impact through a sequence of nudges at different organizational layers. Integrating nudging into current safety practices, guided by cognitive frameworks, offers a holistic approach to safety enhancement. This research contributes practical insights for designing effective workplace safety initiatives, emphasizing the multifaceted nature of safety behavior and the importance of leveraging psychological principles.

Keywords: Nudging; Industrial Safety; Safety Behavior; Layered Nudging; Bounded Rationality

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[1] Costa, S., Duyck, W., & Dirix, N. (2023). *Preventing Hazardous Exposure to Suspended Loads with Nudge Interventions* [Manuscript submitted for publication].

INTRODUCTION

The significance of industrial safety cannot be overstated, as it stands as a pillar of modern society's progress and well-being (Hofmann et al., 2017). Industries, ranging from manufacturing and construction to energy production, play a pivotal role in shaping economies and improving living standards (Stearns, 2020). However, this progress comes with inherent risks that necessitate meticulous attention to safety protocols and ensuring adherence to it. Industrial accidents not only jeopardize the health and lives of workers but can also lead to catastrophic environmental damage (Peterson et al., 2003), economic setbacks (Gavious et al., 2009), and social upheaval (Meshkati, 1998). Through the application of rigorous scientific principles, risk assessment, and the implementation of advanced safety measures, the potential for accidents can be minimized, ensuring the harmonious coexistence of industrial development and human welfare (Beus et al., 2016; Min et al., 2019).

Over the decades, traditional industrial safety approaches have undeniably contributed to improving workplace conditions and reducing accidents. This evolved from technological advancement and better management systems, followed more recently by safety culture (i.e., altering safety norms and values) and behavior-based safety programs (i.e., promoting critical safety behavior through coaching and incentives). Despite their best efforts, industrial safety now seems to have reached a plateau in results obtained with those combined approaches (Hudson, 2007). Research indicates that up to 90% of occupational accidents are human-error related (Kletz, 2001), implying that a better understanding of human errors in interaction with potential hazards (e.g., machinery) can be seen as the last main issue to resolve (Lindhout & Reniers, 2017).

Towards a New Safety Approach: Bounded Rationality and the Practice of Nudging

The evolving landscape of human behavior and decision-making calls for a fresh perspective to enhance the effectiveness of current safety approaches. Enter 'nudging', a concept rooted in behavioral economics and psychology that holds the potential to foster industrial safety (Thaler & Sunstein, 2008).

Unlike traditional approaches that often rely on rules, regulations, and punitive measures, the nudging interventions focus on gently guiding individuals towards safer choices through subtle changes in the physical, social or informational decision context (i.e., choice architecture) (Thaler et al., 2012). Examples are the placement of healthy food at eye level to increase consumption (increasing visibility and salience[2], Bucher et al. (2016)), the use of a citrus odor to promote hand hygiene (priming[3] subconscious associations, King et al. (2016)) or simple reminder messages to reduce the number of 'no shows' at dentist check-ups (countering memory lapses, Altmann and Traxler (2014)). Human behavior is inherently influenced by evolutionary drivers and simple heuristics[4] (e.g., 'follow the group'), that are not optimally aligned with modern-day complexities and therefore lead to systematic deviations (i.e., cognitive biases) from prescribed goals (e.g., safety protocols) (Kahneman, 2011; Tversky & Kahneman, 1974). Instead of ignoring or denying these biases, nudging starts from their acknowledgment and understanding in order to exploit them in reaching the same goal by presenting information or altering environments in ways that nudge individuals towards desired behaviors without compromising their freedom of choice. Humans, for example, have learned implicitly to value social interactions and belonging for a variety of reasons that would enhance survival (Aronson, 1994). While a heuristic 'follow the group' might be beneficial in some occasions (e.g., collective climate preserving actions, see Bergquist et al. (2023)), it can also lead to systematic mismatches (cfr. cognitive biases) that steer behavior in a wrong direction (e.g., the spread of fake news, Van Der Linden (2023)). Social norm nudges have been shown to capitalize successfully on this heuristic by displaying covert information on what the majority of the group values or does (Bicchieri, 2017). One study showed that providing the

[2] Salience is the characteristic of something that stands out from its environment and draws the individual's attention (Taylor & Thompson, 1982).
[3] Priming involves how an initial stimulus can unconsciously affect our response to a subsequent stimulus (Bargh & Chartrand, 2000).
[4] Heuristics, or rules of thumb, are considered an attempt of our brain to deal with an abundance of information in the world relevant for survival. Over the centuries, they have become automated and an integrated part of our decision-making process (Tversky & Kahneman, 1974).

social norm message '75% of the people in this room re-use their towel' was able to foster sustainable behavior (Goldstein et al., 2008). For additional nudging examples, see Thaler and Sunstein (2008) and Sunstein (2014).

The nudging approach aligns with the modern understanding that human decision-making is boundedly rational, meaning that it is deeply affected by social, cognitive, and emotional factors (Simon, 1955). Kahneman's (2011) dual-process theory of decision-making captures this adequately by referring to a 'system 1' that is more automatic, subconscious and instinctive, and a 'system 2' that is more deliberate, effortful and slower. System 1 generates constant implicit impressions of its environment through sensory information and heuristics, and heavily influences the operations of conscious system 2 that only becomes active when situations become more complex[5] (e.g., difficult calculations or deciding which safety protocol to follow). This psychological framework allows us to clarify the underlying mechanisms that drive human behavior and how nudges influence behavior by exploiting system 1 processes (e.g., implicitly linking color to mood, see Tham et al. (2020)) and system 2 limitations (e.g., using reminders to counter the inability to remember everything).

Nudge Effectiveness and Strategic Implementation

Research on nudging underscores its ability to generate significant behavioral changes across diverse domains, including health, finance and sustainability (Bergquist et al., 2023; Raban et al., 2023; Thaler & Benartzi, 2004). For an overview of the average effect sizes and related ongoing discussions, see Mertens et al. (2022), Maier et al. (2022) and Hallsworth (2022). Whether these effects sustain over the long-term has yet to be further investigated (Congiu & Moscati, 2022; Marchiori et al., 2017; Van Rookhuijzen et al., 2021). Nudges often exhibit cost-effectiveness, requiring minimal financial investment compared to traditional approaches. Benartzi et al. (2017) found the return on investment

[5] Captured metaphorically by Kahneman (2011) as 'lazy system 2'

ratios per invested dollar by governments to be much higher for nudges (10 – 100) than for informational and educational campaigns (14.68) or economic tax incentives (1.24). While scholars brought ethical considerations to attention (i.e., regarding individual autonomy and transparency), the current consensus supports ethically sound nudges when aligned with mutually beneficial end goals, such as health and safety (Chowdhury, 2021; Sunstein, 2015).

Nudge Taxonomy: A Guide for Strategic Development

Multiple models and frameworks exist to facilitate behavioral change and nudge development (e.g., EAST, COM-B, MINDSPACE; see The Behavioural Insights Team (2014, April 11), (Michie et al., 2011) and Dolan et al. (2010) respectively). The framework of Münscher et al. (2016) is one of the most comprehensive and entails a taxonomy of nudging clusters and techniques (also called 'choice architecture techniques'), structuring the plethora of nudging interventions that there is today. They define three separate clusters that are based on distinct psychological barriers.

The first cluster, Decision Information, aims to improve the accessibility, clarity and personal relevance of decision-relevant information. Nudging techniques covered, among others, include social norm messages (e.g., "75% of the people reuse their towel"), framing (e.g., physicians advising a medical method with "a 95% chance of success" more than one with "a 5% chance of death", McGettigan et al. (1999)) or feedback on performance (e.g., "Your energy consumption this month was X" or "Your neighbors consumed less energy on average", Allcott (2011)). Second, the Decision Structure cluster capitalizes on the context-dependent nature of decision-making by adjusting the arrangement or format of choice options to shape behavior. Related nudging techniques are the use of defaults (e.g., opting-in versus opting-out policy for organ donations, Davidai et al. (2012)), altering the required effort or experienced resistance for choice options (i.e., ‘friction’, Dooley (2019)) (e.g., increasing or decreasing[6] the convenience for healthy food or tobacco and alcohol respectively to alter consumption, Hollands et al. (2017)) or changing the arrangement or composition of choice options (e.g., sustainable food options on top of the menu are chosen more, Langen et al. (2022)). The final cluster, Decision Assistance, tackles the divide between intention and action by bolstering self-regulation. The objective is to diminish inadvertent behaviors stemming from restricted attention, memory lapses, and a lack of self-discipline. Nudges belonging to this cluster are the use of reminders (e.g., text-based reminder increasing vaccination uptake, Milkman et al. (2021)), salience nudges (e.g., the use of bright-colored tread edge highlighters to improve foot placement and prevent falling, Foster et al. (2014)) and pre-commitment (e.g., increased pension-saving by committing to employer-initiated automatic transfers of a fixed paycheck portion into savings, see Thaler and Benartzi (2004)). By utilizing Münscher et al.'s taxonomy, nudge designers can strategically align nudges with specific goals and psychological barriers encountered.

Nudging Industrial Safety

By integrating nudges into traditional safety strategies, industries can create environments that subtly encourage the adoption of safer behaviors. Although by definition multiple safety interventions qualify as nudges (e.g., use of signs, arrows or colors), to date very few studies exist that examine the potential of nudges as a complementary safety approach (Lindhout & Reniers, 2017). The few explored safety nudges are largely situated in the domain of traffic safety. One study found that smiley faces can increase the effectiveness of speed feedback displayed on digital speed signs (cfr. emotional influence system 1) (Gehlert et al., 2012). Despite their potential, industrial safety, nudge studies remain scarce,

[6] While nudging reduces the friction surrounding actions that benefit people, the related term ‘sludge’ has been coined for the opposite, interventions increasing friction that impede the appropriate actions (e.g., long text formats to make people agree on the terms without carefully reading it) (Sunstein, 2022b).

limiting our understanding of their full impact. Some studies do describe industrial safety interventions that can be defined as nudges, such as the use of yellow tread highlighters to promote foot placement on stairs (Foster et al., 2014) or text reminders for supervisors to promote the frequency of safety talks on a construction site (Rice et al., 2022); but they all lack a compelling framework (cfr. nudge theory and system 1 & 2) to classify all interventions based on the underlying psychological mechanisms.

Multiple Lines of Defense

When developing industrial safety nudges, it is important to incorporate established insights from the most recent safety models on human error and human factors (Lindhout & Reniers, 2017). Several renowned safety models show the complex interplay of factors leading to an accident. The Human Factors Analysis and Classification System (HFACS) categorizes factors affecting safety into four levels: organizational influences (e.g., suboptimal processes), unsafe supervision, pre-conditions for unsafe acts (e.g., employee knowledge, fatigue or bad weather) and unsafe acts (e.g., intentional violations or unintended error) (Shappell & Wiegmann, 2001; Wiegmann & Shappell, 2001). It offers a structured approach to dissect and mitigate factors contributing to accidents in complex systems (see Figure A1 in the Appendix for a representation of the model). This HFACS model is largely inspired by Reasons' Swiss Cheese Model (Perneger, 2005; Reason, 1990; Reason, 2000), which populated the idea that safety exists out of multiple layers and that accidents only occur because of flaws in every layer ('through the holes of multiple superimposed cheese slices' hence the metaphor, see Figures A2 and A3 in Appendix for a visual representation). Implementing and improving multiple lines of defense (e.g., better organization, supervision or training) should be able to prevent accidents in different stages, from early contributing organizational factors (e.g., insufficient safety investments) to direct leading factors on the work floor itself (e.g., distraction). Multiple nudge interventions should aim to target multiple lines of defense, simultaneously or sequentially, to surpass their smaller individual effects and to leverage the tendency of higher combined effects (or 'additivity') found in multiple studies (Ayal et al., 2021; Brandon et al., 2019).

CURRENT STUDY

Typically, working at height, handling heavy loads, contact with moving machine parts, gas hazards and traffic safety account for the largest proportion of accidents (up to 75%) in the process industry (Lindhout & Reniers, 2017). Given that, up to 90% of all occupational accidents are related to human errors (Kletz, 2001), this is an unexplored promising avenue. In this study, we explore the nudging potential in the domain of handling heavy loads through a series of field experiments in a large Belgian steel plant employing over 5000 employees. More specifically, we investigate if nudges can help workers to keep a safe distance to suspended heavy loads (e.g., steel coils or heavy machine parts). Mishandling or insufficient precautions during load movement can lead to life-threatening injuries, equipment damage, and production disruptions (de la Colina & Cervera, 2016; Häkkinen, 1982). Moreover, the complex and dynamic nature of such tasks demands precise adherence to safety protocols (OSHA, 2010b). Three experiments are carried out to evaluate the effectiveness of nudges in reducing behavioral flaws in multiple lines of defense-related to hazardous suspended load exposure (cfr. HFACS and the Swiss Cheese model); focusing mainly on multiple lines of defense on the same layer of 'unsafe acts' (Figure A1 in Appendix) and therefore using a more horizontal approach[7]. A set of observations and interviews is performed one month in advance to determine relevant psychological barriers and environmental factors. For all experiments, we selected the most fitting design, accounting for a multitude of constraints in real-life settings (e.g., sparse eligible locations, confounding influences and budget and time limitations).

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[7] As opposed to a vertical approach that would use nudges to target flawed decision-making on multiple different layers of the hierarchy (e.g., nudging unsafe acts, unsafe supervision and organizational decision-making). While this vertical approach is highly relevant, it falls out of the scope of the current study (because of its feasibility).

Experiment 1 - Following Safe Pathways

The first experiment aims to nudge people in following the designated safe paths in the factories, guarding them from falling loads, entrapment and other potential hazards (e.g., contact with moving machine parts). Several behavioral elements play a role in adhering to this safety protocol, such as the visibility of the of the safe paths (e.g., green color), their logical and time-efficient placement in the factory and the social influence of colleagues complying with tracks or not. This experiment focuses on social norms that play a pivotal role in influencing safety behavior because people often adhere to what their peers do, trying to fit in with the group (cfr. herd behavior and conformity, see Banerjee (1992) and Asch (1956) respectively). A distinction can be made between descriptive norms (i.e., what people actually do, also called 'social proof') and injunctive social norms (i.e., what people value or deem appropriate). Research has shown that descriptive norms play a bigger role in influencing an individual's own decision, whereas injunctive norms play a bigger role in influencing recommendations to others (Zou & Savani, 2019). Moreover, norm nudging appears to be more effective when it entails norms of one's local setting and circumstances (i.e., 'provincial norms', see Goldstein et al. (2008). The nudge tested in this experiment includes a descriptive norm (or social proof) nudge displaying data (i.e., a digital sign) of the number of colleagues using the safety pathways to create a positive peer influence (i.e., increasing the access to decision-relevant social information, cfr. cluster Decision Information). We believe this nudge will lead to a small significant increase of people using the safety pathways, in line with the norm nudging literature (Hypothesis 1) (Bicchieri, 2017).

Experiment 2 - No-Touch Tools

The second experiment investigates a holistic approach to increase the use of no-touch tools, which are devices designed to enable hands-free operation of equipment or processes (e.g., a stick or a rope). The aim of these tools is to reduce the risk of injury by minimizing direct contact with potentially hazardous machinery or materials. This experiment aims to address flaws in multiple lines of defense with both nudges and more standard (safety) interventions combined, which to date, is generally investigated separately (Beshears & Kosowsky, 2020). A first intervention involves the mere communication of supervisors to the workers that no-touch tools are of paramount importance for safety and should be used consistently where possible[8]. By using their supervisor as a messenger (i.e., increasing the relevance, cfr. Decision Information), at least a small effect of this message is expected (Hypothesis 2), in line with the literature of messenger effects (Hafner et al., 2019). Secondly, previous studies have shown that altering the placement of a product might increase its usage (e.g., increased consumption of healthy food; see Bucher et al. (2016)). By placing the no-touch tools closer to the workstations (i.e., reducing friction and effort, cfr. Decision Structure), that are currently often centralized in the workplace of the industrial plant, we expect a small significant effect on its usage (Hypothesis 3). Given that the decision structure cluster is typically considered the most effective of all three (Mertens et al., 2022), a slightly bigger effect is expected for the placement than for the communication (Hypothesis 4). Another important element that came up during the interviews was that some of these tools are considered impractical to use (e.g., a thick rope of 8m to guide a load). Based on the input of the workers on potential better equipment during a brainstorm, some new tools are introduced at the work floor (i.e., a more typical safety intervention of introducing new tools, together with allowing participation) and expected to have a small to medium effect on their usage (Hypothesis 5). By working on multiple aspects of no-touch tool compliance (cfr. multiple lines of defense), we aim to maximize the effect towards behavior change.

[8] To date, there is no strict obligations for using no-touch tools, safeguarding worker autonomy and exploring non-intrusive interventions before installing obligations and control mechanisms (that require consistent supervision).

Experiment 3 – Visibility and Awareness of Suspended Loads

The third experiment addresses a different aspect contributing to hazardous exposure to suspended loads, namely the compromised awareness of nearby employees and suspended load visibility. Heavy loads are often transported over larger distances, from a couple to hundreds of meters, inside or nearby the factories. While risk zones are often indicated with restricted access, people often have to pass or work nearby suspended moving loads. The nudge in this experiment aims to promote awareness in order to keep distance to the suspended load (cfr. 'triangle principle' handled by the industrial plant, distance should be proportionate to the height, see also VESI (2016), OSHA (2010a) and OSHA (2016)) by projecting a red and white light circle beneath the load. This light projection aims to increase the salience of the suspended load by directing attention towards it (i.e., supporting attention with environmental cues, cfr. Decision Assistance). By adding a red color, it is also expected to signal and prime potential danger, leading to increased risk perception and subsequent safety behavior (Luximon et al., 1998; Pravossoudovitch et al., 2014). Both directing attention and priming safety behaviors target system 1 processes directly. In addition, the light circle provides guidance on how far people exactly should stand when working nearby (cfr. triangle principle), which on sight is not always easy to determine (or at least prone to errors). We believe that projecting light circles will draw attention to the load's presence and potential hazards, having a small significant effect on workers keeping more distance (Hypothesis 6). As during the pre-observations, one month in advance, we noticed that people might act differently in group (e.g., older colleagues entering the circle and younger colleagues following suit), we expect that the effect on compliance might be different for individuals in group (Hypothesis 7).

EXPERIMENT 1

The industrial plant involved in this study processes iron ores into finished products through a variety of large departments, including raw materials, cokes factory, steel factory, hot-rolling mill, cold-rolling mill, galvanization lines, general services (i.e., maintenance) and refining departments (i.e., making detailed end-products). The first experiment takes place in the Cold-Rolling Mill (CRM) where many heavy steel coils (e.g., 30 tons) are transported with cranes along the factory.

Method

Participants

The participants include the employees of the CRM, with the exception of some external employees of other departments or contractors passing-by (a maximum of 5%). At the CRM there are four shifts[9] guaranteeing continuous staffing for constant production. Every shift employs around 120 workers, with approximately 480 to 500 workers on a daily basis (mainly male blue-collar workers). The internal employees of the CRM (N= 597) have a mean age of 43.35 years (SD = 11.59) and mean seniority of 19.88 years (SD = 12.61). A total of 11 360 observations is collected using camera footage (preventing potential Hawthorne effects). Before starting this study, approval is obtained from the labor unions representing all employees, informing them about the content of the study, interventions and privacy implications. Summaries of the results are freely accessible for the employees on their intranet website. Ethical clearance for this study is provided by the safety department of the industrial plant.

Design and Procedure

A within-subjects design is used, including a baseline measurement of 2 weeks (control), followed by a test measurement (active social proof nudge) in the subsequent third, fourth and fifth week. The social proof (or descriptive norm) nudge involves a digital sign that counts and displays the

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[9] Three rotating shifts (morning 6:00-14:00, evening 14:00-22:00 and night 22:00-6:00) and a day shift (8:00-16:00)

number of workers that used the safe pathway that day and that month. Note that we deliberately decided to only display the amount of people that used the safe road, and not the ones that do not to prevent adverse social norm effects (in case the majority would not comply). A permanent message on top of the sign says "Together safe on the green path" in Dutch (see Figure 1)[10]. A camera is used to observe the number of passersby using the safe path, when passing in the direction facing the sign (i.e., the main direction of passersby).

Data Analysis

Binary logistic regression analyses are carried out to analyze the binary dependent variable (using the safe path = 1 or not =0) among control and test conditions. The odds ratio (small 1.5, medium 2.5 and large 4; see Chinn (2000), Hasselblad and Hedges (1995) and Sánchez-Meca et al. (2003)) and Cohen's D (0.2 = small, 0.5= medium, 0.8 = large) are calculated as effect size measures. The statistical analyses are conducted using IBM SPSS Statistics version 27.

Figure 1

A digital sign displaying the number of passersby on the safe pathway

[10] While the green color of the path in Figure 11 for a large part decayed, 'green path' remains a consistently used and known term to the employees of the industrial plant (i.e., a synonym for 'safe pathway')

Results

The results of the binary logistic regression can be found at Table 1. They show that, consistent with our prediction, the social proof nudge has a positive significant effect on the usage of the safe path. In contrast to our hypothesis, the effect of the social proof nudge is not small but large for the first week with an OR of 3.80 (p < .01, 95% CI: 3.30 - 4.38), even higher in the second week with an OR of 4.87 (p < .01, 95% CI: 4.20 - 5.64) and the highest in the third week with an OR of 5.36 (p < .01, 95% CI: 4.57 - 6.29). The Cohen's D is equally provided in Table 2 as an alternative effect size. Figure 2 represents the number of passersby using the safe path in percentage per condition.

Table 1

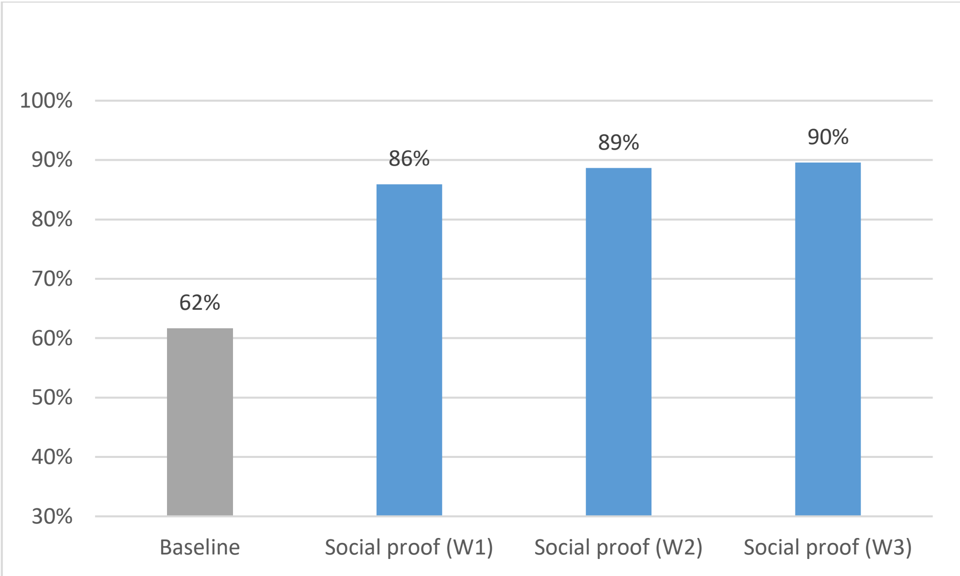
The results of the binary logistic regression (Experiment 1)

VARIABLES	Usage safe path		
	Exp (B)	95% C.I.	*d*
Social proof (week 1)	3.80*** (18.56)	3.30 - 4.38	*0.74*
Social proof (week 2)	4.87*** (21.11)	4.20 - 5.64	*0.87*
Social proof (week 3)	5.36*** (20.48)	4.57 - 6.29	*0.93*
Observations	11 360		

Note. z-statistics in parentheses; *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Baseline (control)'.

Figure 2

The number of people using the safe pathway (in %)



Discussion

The results indicate that a social proof nudge can lead to a large significant increase of employees using the safe pathways by displaying descriptive norms (i.e., what are colleagues actually doing); which is larger than the typical small to medium effect we can expect from the literature (Bergquist et al., 2023; Bicchieri, 2017). A potential moderator can be the (private) company context, as opposed to nudges more commonly investigated in the public domain (Kubera, 2023), and forms a promising avenue for further research. Note that displaying only the frequency of desired behavior, in contrast to both desired and undesired (i.e., not following the safe paths), can be strategic when the undesired behavior has a chance to be more prevalent (i.e., preventing reversed social norms effects) (Cialdini et al., 2006). While in our study, many of the participants were not aware of the identity of other people in the sample (i.e., workers from other shifts or subsections), in less populated settings, the visible compliance with the safety rules ("What do the workers in front of me?") can receive a greater weight (cfr. local or provincial norms, see Goldstein et al. (2008)). This can moderate the effect of a sign displaying the amount of people complying (e.g., "I know how it is done in practice, you cannot fool me"). In addition, the effect of the social proof nudge seems to remain stable and even slightly increase in the subsequent weeks. It is plausible to assume that this slightly increasing trend is related to the increasing number of complying employees displayed at the sign, as the sign shows both passersby on a daily and monthly basis.

EXPERIMENT 2

The second experiment takes place at the central workshop of the General Services (GS) department. This department takes care of the maintenance of machine parts, including heavy ones that need to be lifted on workstations and transported inside the warehouse. Therefore, no-touch tools are advised to use.

Method

Participants

The participant sample consists solely of internal workers from the central workshop of the GS department. A total of 52 participants work there, all working during a day shift. The workers are all male with a mean age of 43.99 years (SD = 11.85) and mean seniority of 19.72 years (SD = 11.38). A total of 500 observations is collected by two trained independent observers from a higher-located office space, invisible to the workers, with an overview of all workstations of the warehouse. The procedures for obtaining ethical approval and providing feedback to the employees were identical to Experiment 1.

Design

A within-subjects design is used, including a baseline measurement (control) and four subsequent test conditions (communication, placement of no-touch tools, new tools implementation and long-term follow-up). Every condition lasts one week, with 5 weeks in total (with the long-term follow-up taking place 6 months later). The communication condition includes an email sent by their supervisor (i.e., line manager) displaying a photo of the no-touch tools (see Figure 4) and the following message “Handling suspended heavy loads contains a high safety risk, therefore we strongly advice and expect you to use the no-touch tools where possible” in Dutch. A brief verbal repetition of this message was also provided at the beginning of the week. The placement condition includes moving the current no-touch tools from a central point in the warehouse to every workstation individually (reducing a 2 minute walk to seconds) (see Figure B1 in Appendix 5B for the indication on the work shop floor plan). For the last test condition, the old no-touch tools (see Figure 3 and 4) are replaced with new ones, based on input received during the preparatory interviews and observations performed one month in advance. The need for better, more stable and practical tools was mentioned and met by the new set of tools (see Figure 5 and 6). The long impractical rope to guide suspended loads is replaced by a dog leash that rolls up the excess rope automatically, a creative solution cleared by the safety department[11]. These new tools are again placed nearby the workstations. A long-term follow-up is carried out 6 months later (i.e., one week of observations), with the new tools and their altered placement nearby the workstations remaining active. Binary logistic regression analyses are carried out to analyze the binary dependent variable (using the no-touch tools = 1 or not = 0, on every occasion where a no-touch could be used) among control and test conditions. The odds ratio and Cohen’s D are calculated as effect size measures.

[11] Such a rope or leash allows employees to guide a suspended load over a longer distance and at times more flexible use than sticks, but is of course restricted to pulling actions

Figure 3

An example of a suspended load

Figure 4

The old no-touch tools

Figure 5

The usage of the new dog leash

Figure 6

The new no-touch tools

Results

The results of the binary regression analysis in Table 2 show that all interventions, except for the communication intervention (i.e., the line manager highlighting the importance of no-touch tools), had a positive significant effect on the usage of the no-touch tools. Inconsistent with our prediction, the effect of the communication is insignificant with an OR of 1.65 ($p > .05$, 95% CI: 0.52 - 5.24), while at least a small positive effect was expected. A large significant positive effect is found from the placement nudge on the use of no-touch tools with an OR of 10.23 ($p < .01$, 95% CI: 0.52 - 5.24). This effect increases significantly when in the subsequent condition new tools are combined with better placement, involving an OR of 99.75 ($p < .01$, 95% CI: 35.04 - 283.97), and holds largely over a period of 6 months with an OR of 76 ($p < .01$, 95% CI: 27.29 - 211.63). See Figure 7 for a representation in percentages of the amount of people using the no-touch tools among all conditions.

Table 2

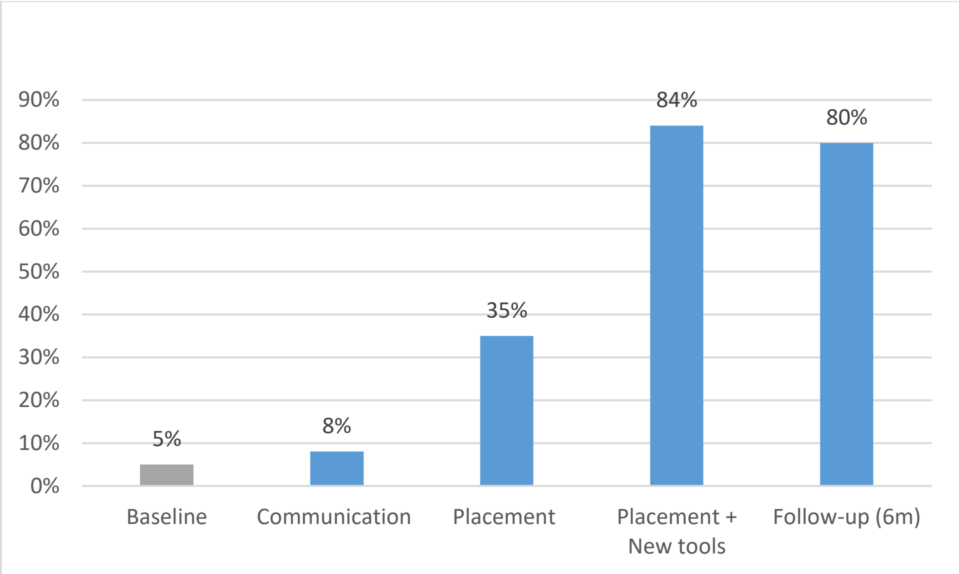
The results of the binary logistic regression (Experiment 2)

VARIABLES	Usage safe path		
	Exp (B)	95% C.I.	*d*
Communication	1.65 (0.85)	0.52 - 5.24	*0.28*
Placement (friction)	10.23*** (4.61)	3.81 - 27.50	*1.28*
Placement + New tools	99.75*** (8.62)	35.04 - 283.97	*2.54*
Follow-up (6m)	76*** (8.28)	27.29 - 211.63	*2.39*
Observations	500		

Note. z-statistics in parentheses; *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Baseline (control)'.

Figure 7

The amount of people using the no-touch tools (in %)



Discussion

All of the interventions appeared to increase the use of the no-touch tools significantly, apart from the communication of the supervisor highlighting its importance. At least some effect of the message was expected given the associated messenger effect (Hafner et al., 2019). The effect of the message might have been bigger if it was conveyed by more closely related supervisors (e.g., foremen or team leader) instead of the line manager ('n+1' or direct supervisors have shown to exert a bigger influence, see OECD (2020)). The placement nudge that reduced friction (cfr. Decision Structure) had a large effect, which is greater than expected (Dooley, 2019); implying that altering minimal efforts such as tool placement can have a big effect. Although the increased visibility likely had some moderating effect (Wansink et al., 2006), it is considered minimal given the absent difference in the baseline for workstations that had the tools in sight. The introduction of better tools, acquired through bottom-up input, had a large effect that even exceeded our optimistic medium-sized prediction. Because this intervention consists of multiple elements (i.e., placement, participation and technological innovation), further research is needed to clarify the most active component (or interaction). It does show that nudges (e.g., placement) are compatible with more traditional safety interventions (e.g., better tools and participation), and combined lean towards a promising holistic approach (Lindhout & Reniers, 2017). Another promising element is that the effect largely holds over a 6 month period, which is crucial for solid safety management (Krause et al., 1999) and sparse among behavior change initiatives (Beshears & Kosowsky, 2020).

EXPERIMENT 3

The third experiment takes place at one of the refining departments, Steel Decoration (SD), where decorative steel parts are produced and steel coils are packed for transport. These heavy steel coils are transported by cranes and lifted to the appropriate spot for packing. This can lead to dangerous exposure to the suspended loads when the safe distance is not respected.

Method

Participants

The sample exists out of 36 external workers from the SD department (i.e., packing and transporting coils outsourced to an external firm). The workers are all male with a mean age of 38.62 years (SD = 10.12) and mean seniority of 13.05 years (SD = 12.79). A total of 516 observations of workers transporting heavy loads is collected using camera footage[12]. The procedures for obtaining ethical approval and providing feedback to the employees were identical to Experiments 1 and 2.

Design

The third experiment has a within-subjects design with a baseline measurement (i.e., control) followed by a test condition (i.e., light projection beneath load) and a follow-up one month later (i.e.,

[12] Exceeding the necessary sample size of 361 to find a small effect prescribed by the power analysis (using G*Power)

light projection remaining active). All three conditions last one week. A light projector is added to the crane and is activated once the crane picks up a load (i.e., by pressing on two push button on the hook using gravity). A red and white circle is projected beneath the load, which adapts to the height by increasing the circle's diameter (cfr. triangle principle; see Figure 8). In this experiment, we observed if workers and passersby keep their distance from the load (i.e., not entering the projected circle) when it is moving to and hanging above the workstation. Binary logistic regression analyses are carried out to analyze the binary dependent variable (standing outside the red circle = 1 or inside = 0; with a 0 given to an individual entering the circle minimum one time per transfer, with two transfers per steel coil that come and go) among the control and test condition. The odds ratio and Cohen's D are calculated as effect size measures.

Figure 8

A red-white light projection of a circle beneath the suspended load

Results

Table 3 displays the results of the binary regression analysis. These results indicate, consistent with our predictions, that the light projection (i.e., salience nudge) has a significant positive effect on keeping distance to the suspended load (i.e., outside the red circle) when compared to the baseline. In contrast to our hypothesis, the effect is large instead of small with an OR of 7.16 (*p* < .01, 95% CI: 2.35 - 21.83). This effect remains large and significant over a period of one month, but seems to know a small decline with an OR of 4.14 (*p* < .01, 95% CI: 0.08 – 1.63). Based on the observations using camera footage, it appears that workers who are not complying often try to perform an action (e.g., scanning the coil) before the coil hits the ground or to correct an action when the coils is already lifted of the ground (e.g., adjusting the packaging of the coil). Because our pre-observations indicated social influence from colleagues could play a role, we looked at the impact of being in group (i.e., at least with two persons), but found no significant effect on keeping distance to the suspended load with an OR of 0.37 (*p* > .05, 95% CI: 0.08 - 1.63). Figure 9 represent the percentage of people outside the red circle when near a suspended load for all conditions.

Table 3

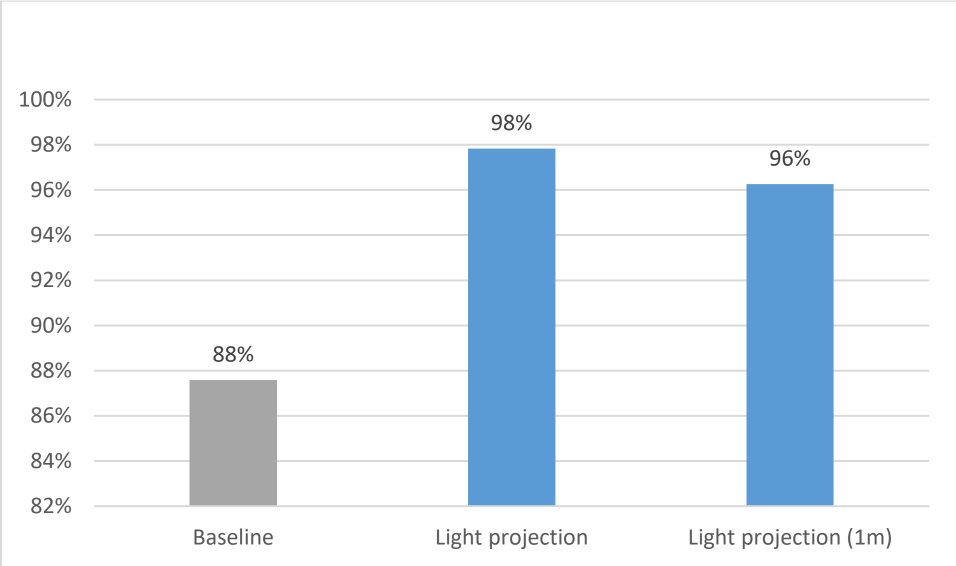
The results of the binary logistic regression (Experiment 3)

VARIABLES	Usage safe path		
	Exp (B)	95% C.I.	*d*
Light projection	7.16*** (3.46)	2.35 - 21.83	*1.09*
Light projection (1m)	4.14*** (3.05)	1.66 - 10.31	*0.78*
Group	0.37 (-1.32)	0.08 - 1.63	*-0.56*
Observations	516		

Note. z-statistics in parentheses; *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Baseline (control)'.

Figure 9

Amount of people standing outside the projected red-white circle (in %)



Discussion

The projected red and white circle beneath the suspended load successfully nudges employees to keep their distance, almost reaching full compliance (98%). This aligns with previous research indicating that making the desired action more salient can have a positive effect (cfr. Decision Assistance), but the effect is considerably higher than expected (Ischen et al., 2022). One potential reason is the obvious personal and direct benefit of safe actions in a high-risk situation that can moderate the salience effect (although this varies among individuals with different personality traits, Beus et al. (2015)). Another likely reason is the cumulative effect of combined elements, including salient aspects, but also increased visibility of unsafe actions (cfr. social norms) and the adaptive feedback element of the light projection. In fact, our findings suggest that providing feedback, involving the adaptive diameter of the circle relative to the height, can assist in deciding how far 'far enough' is exactly (cfr. Decision Information) (Cappa et al., 2020). Yet, further research should confirm this by investigating a projected circle with and without adapting to the height to define the added value of the feedback component. Encouraging is that the effect persists largely one month later; further follow-ups will have to determine whether the effect lasts in the long-term. In addition, previous studies have shown how a red color can prime danger (Pravossoudovitch et al., 2014), however, further experimentation will have to indicate if the red color is determining for the effect of the light projection or if other colors (e.g., blue) work as well.

GENERAL DISCUSSION

This study contributes to the applied understanding of nudging strategies within industrial contexts and offers insights into the potential of specific interventions to influence safety practices concerning suspended loads. Ultimately, the results will aid in designing more effective workplace safety initiatives and contribute to the ongoing discourse on enhancing occupational health and safety.

Nudging Distance to Suspended Loads

One of the central findings of this study is the effectiveness of various nudging interventions in increasing the distance to suspended loads. These interventions encompassed a range of strategies, each with its unique approach and rationale.

The deployment of a digital sign showing the frequency of colleagues using the safe path is rooted in the concept of social proof (or descriptive social norms) (Cialdini, 2013). This powerful psychological principle suggests that individuals are more likely to emulate behavior they perceive as the norm (Bicchieri, 2017), capitalizing on the evolutionary need for social inclusion and relatedness (cfr. system 1) (Aronson, 1994; Deci & Ryan, 2000). In this context, the digital sign displays those (covert) norms visually (cfr. Decision Information) and it appears that, as the displayed frequency increases, workers are increasingly (be it slightly) motivated to follow suit. This implies that social proof interventions become more effective when representing a larger (proportion of a) peer group, which is consistent with what we would expect based on the literature (Cialdini et al., 2006). By harnessing the power of social norms, one could facilitate the development of a new safety culture that is more adept to modern safety requirements (Naji et al., 2022).

The placement of no-touch tools is a practical example of reducing friction, which comes down to subtly altering the required effort (or the perception of it, Dooley (2019)). By making safe choices more convenient and altering their utility through rearrangement (cfr. Decision Structure), this intervention eliminates some of the obstacles that may have previously deterred workers from adhering to safety protocols (cfr. notifying and removing 'sludge', see Sunstein (2022b) and Thaler (2021)). Moreover, the combination of the placement with more standard safety interventions, such as better tools developed through bottom-up brainstorming, had a remarkable effect, reaching an impressive 84% usage. This underscores the potential synergy between nudge-based approaches and more technical, worker-driven safety initiatives (Lindhout & Reniers, 2017). Further testing should refine what degree of the effect originates from the better tools themselves in relation to the bottom-up approach and convenient and visible placement.

The use of a salient light projection (cfr. Decision Assistance), providing real-time feedback on the exact distance relative to the height of the suspended load (cfr. Decision Information), proved to be an incredibly effective nudging intervention. Increasing the salience of the suspended load makes the workers acutely aware of their proximity to potential dangers, requiring little cognitive effort and thus drawing mainly on system 1 processing. This has the advantage that in cognitive demanding situation, common for industrial settings (i.e., fatigue, taxing work conditions, difficult taks or time pressure; related to 'cognitive load', see Sweller (1988) and Aldekhyl et al. (2018)), workers are still being nudged to safety, while system 2 depending processes (e.g., actively monitoring every risk) might run out of fuel, fail and fall back on system 1 ('willpower as a limited resource', cfr. 'ego depletion' and the exhausted system 2, see Kahneman (2011)). By achieving nearly full compliance at 98%, this nudge intervention demonstrates the power of real-time, context-sensitive feedback (Buckley, 2020) and attention-drawing environmental cues (Wilson et al., 2016) in influencing safety behavior.

Furthermore, the longevity of the effects observed in this study is noteworthy. All interventions retained their effectiveness over an extended period (i.e., varying from one to six months, and counting), indicating that the impact of nudges and nudge combinations with standard safety interventions extend beyond short-term compliance (a delicate matter in the nudging literature that remains poorly understood, see Hallsworth (2023), Marchiori et al. (2017) and Thaler (2021)). This has significant implications for workplace safety, as sustained adherence to safety practices is paramount in preventing accidents and injuries (Krause et al., 1999; Spigener et al., 2022).

A Layered Nudging Approach

The reasoning advocated by Reason's Swiss Cheese model (Perneger, 2005; Reason, 2000) and HFACS (Shappell & Wiegmann, 2001) to reinforce multiple lines of defense can be extended to nudge applications. The findings of this study indicate that nudges can promote multiple facets (e.g., following safe paths, using no-touch tools and keeping distance) that contribute to hazardous exposure to suspended loads and call for the adoption of an integrated nudging approach that consistently targets multiple lines of defenses in industrial safety contexts. We propose a new concept of 'layered nudging' as a new promising way forward, discriminating between horizontal and vertically layered nudging strategies.

Horizontally layered nudging, as demonstrated in this study, involves multiple small nudges that collectively mitigate risks on the same implementation level or layer. Using the example of the hierarchical HFACS model (Figure A1 in Appendix), this can involve multiple nudges targeting unsafe acts of workers on the work floor (layer 'unsafe acts'), or multiple nudges that aim to promote the frequency and quality of supervision (layer 'unsafe supervision'). For instance, workers may initially be nudged to follow safe paths using digital signs (utilizing social proof). If compliance remains suboptimal, they might receive additional nudges, such as a salient cue to maintain a safe distance through light projections beneath moving suspended loads. By implementing multiple small nudges simultaneously (or rapid succession), the eventual likelihood of accidents can be significantly reduced through the cumulative effect of nudges (i.e., targeting different behavioral barriers) that has been found in previous studies (Ayal et al., 2021; Brandon et al., 2019; Wilson et al., 2016).

On the other hand, vertically layered nudging targets agents in different layers of an organization (i.e., managers, supervisors, workers, etc.), not only targeting the last person to perform an unsafe action (typically 'the common man', while more voices rise to equally 'nudge the nudger', see Dudley and Xie (2022) and House et al. (2022)). Vertical layered nudging thus targets multiple layers of defense sequentially, in contrast to horizontally layered nudging that implement multiple nudge interventions on the same line of defense (e.g., unsafe acts of workers as a result of interaction with the direct work floor environment). Nudging supervisors to conduct more safety talks (Rice et al., 2022), for example, can increase safety awareness among those workers (Hoonakker et al., 2005) and keep safety top of mind (cfr. WYSIATI[13] or the availability heuristic, a mental shortcut relying on immediate or recent examples of information that come to mind to form thoughts and guide subsequent action, see Kahneman (2011)). These talks can amplify the motivation for using safe paths, increasing the susceptibility to our nudge visualizing social norms using a digital sign (i.e., people who have stronger preferences for something are more easily nudges, and vice versa, see de Ridder et al. (2022)). They might also enhance responsiveness to a salient light projection beneath suspended loads (here serving as a reminder), as research on the availability heuristic shows that recent accidents (and presumably also related talks about risk) largely influence future risk estimations and subsequent safety behavior (Slovic, 2000).

[13] WYSIATI ('What You See Is All There Is')

Both layered nudging approaches hold the potential to tackle popular nudge criticism of generally small effect sizes (DellaVigna & Linos, 2022) and to elevate current safety management by countering flawed decision-making on multiple levels contributing to occupational (fatal) accidents (Shappell & Wiegmann, 2001; Vierendeels et al., 2018).

Integrating Nudging in Current Safety Practice

The integration of nudging, particularly through a layered approach, into current safety practices represents a holistic and multifaceted approach to enhancing safety behavior in industrial settings. This approach recognizes that safety is influenced by a complex interplay of factors, including culture, technology, and management (Reason, 2000; Shappell & Wiegmann, 2001; Vierendeels et al., 2018).

The practice of nudging and associated techniques (Thaler & Sunstein, 2008), as well as Kahneman's (2011) metaphorical two systems of decision-making (i.e., system 1 and 2), provides a valuable framework for understanding safety behavior at a deeper level. Nudging can effectively target both systems, making safety decisions more automatic (system 1) while also promoting and assisting timely conscious deliberation when needed (system 2). By aligning nudging strategies with these cognitive processes, organizations can create a more comprehensive and effective approach to safety (Lindhout & Reniers, 2017).

Moreover, the clusters of Münscher et al. (2016) (i.e., Decision Information, Decision Structure and Decision Assistance) offer a taxonomy for categorizing existing and future nudging interventions (or 'choice architecture interventions') in the realm of industrial safety. These clusters help identify and strategize nudge development based on relevant psychological barriers and allow for meaningful comparison of which nudging techniques worked in what contextual conditions for which target audiences (cfr. a 'heterogeneity approach', indicated as the way forward by nudging experts, see Bryan et al. (2021)). In essence, Münscher et al.'s framework provides a roadmap for tailoring nudges to specific organizational contexts and psychological profiles, thereby optimizing their impact.

Limitations and Further Research

While this study has provided valuable insights into the potential of nudging in industrial safety, it is essential to acknowledge its limitations and avenues for future research.

Firstly, future (lab) studies could address the inherent constraints that are present in field studies, which have impact on the feasibility of certain designs (Cartwright, 2007; Samek, 2019). For example, the incorporation of additional between-subject control groups, in addition to the within-subjects baseline measure, could further validate the observed effects and enhance the robustness of the findings. Additionally, certain test conditions consisted of the simultaneous manipulation of multiple elements or interventions (e.g., colored light projection providing feedback; placement and new tools). To refine the implementation of these interventions, future research should aim to discriminate the most active components within them by dissecting and testing variations of the most successful applications. Also, a lower baseline can play a role, for example, 5% in the current study for the no-touch tools (being impractical or outdated), making re-evaluation of the interventions in contexts with a higher initial compliance rate (e.g., between 20 – 50%) important. Beshears and Kosowsky (2020) indicate that both field and laboratory research should be used as complimentary methods to advance empirical nudging literature by meeting each other shortcomings (i.e., external versus internal validity).

Secondly, this study focused more on a horizontal layered approach, targeting multiple barriers on the same hierarchical 'layer' (i.e., unsafe acts of workers, cfr. HFACS), in different but related contexts relevant to hazardous exposure to suspended loads. Future research should evaluate the effect of the horizontal layered approach at intersections where all nudges are active simultaneously, or in rapid succession, to evaluate its combined effect on safety behavior (e.g., in the same department). The vertical approach remains to be explored, as most nudge studies target the behavior of the final person in line directly (e.g., worker performing unsafe acts) (Dudley & Xie, 2022; House et al., 2022). While this is equally a cornerstone of nudging (i.e., 'influencing the problematic behavior directly'), it also entails a narrow-minded vision on how 'problematic behavior', such as unsafe behavior, occurs and can be prevented (Shappell & Wiegmann, 2001; Vierendeels et al., 2018). By targeting suboptimal decision-making on all layers of the organization hierarchy (i.e., multiple lines of defense), leading directly or indirectly to an undesired outcome, the nudging approach incorporates 'system thinking', which is deemed invaluable for lasting behavior change and further advancement of the behavioral science field (Hallsworth, 2023). This also includes further investigation of how nudges interact with standard safety interventions (e.g., resource allocation, campaigns, coaching and incentives), highlighted as a point of attention in the recent synthesis of nudging literature by Beshears and Kosowsky (2020).

Lastly, the scalability of the interventions to different locations and contexts remains an important area for investigation (DellaVigna & Linos, 2022; Hallsworth, 2022). Context is key, but its effect on nudging remains enigmatic (Bryan et al., 2021; Marchiori et al., 2017). More research is needed that defines (industrial) contextual moderators and mediators of nudge effectiveness (Sunstein, 2022a), other than the presence of strong preferences ('for' or 'against') that correlate with 'nudgeability' (de Ridder et al., 2022). Consistently, post-surveys of participants to examine their internal thoughts and perceptions regarding the interventions would provide valuable qualitative data. Understanding how workers perceive and react to nudges can inform the design of more tailored and effective interventions (Mills, 2022) and might clarify the moderating role of reflection (cfr. 'nudge plus', see Banerjee and John (2021)).

CONCLUSION

This study underscores the potential of nudging strategies to enhance safety practices in industrial settings. Various nudging interventions, including social proof, friction and salience, effectively increased distances to suspended loads, ensuring improved workplace safety. Crucially, these effects persisted largely over time, solidifying nudging's role as a sustainable safety measure. The call for a layered nudging approach, comprising horizontal and vertical strategies, emphasizes the multifaceted nature of safety behavior. By addressing various dimensions of safety simultaneously, this approach minimizes risk by countering flaws in multiple lines of defense. Integrating nudging into current safety practices, guided by cognitive frameworks and psychological principles, offers a holistic safety improvement strategy. Still, further investigation of the scalability, contextual moderators and the persistence of nudge effects over time is needed.

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CHAPTER 6

THE OPPORTUNITIES AND COSTS OF AI IN BEHAVIORAL SCIENCE[1]

This article discusses the opportunities and costs of AI in behavioral science. We argue that because of pattern detection capabilities, modern AI will be able to identify (1) new biases in human behavior and (2) known biases in novel situations. AI will also allow behavioral interventions to be personalized and contextualized, and thus produce significant benefits. Finally, AI can help behavioral scientists to 'see the system,' by enabling the creation of more complexand dynamic models of human behavior. While these opportunities will significantly advance behavioral science and offer great promise to improve the lives of citizens and consumers, wehighlight several costs of using AI. We focus on some important environmental, social, and economic costs that are relevant to behavioral science and its application. Some of those costs involve privacy, others involve manipulation.

Keywords: Artificial Intelligence; Behavioral Science; Bias; Noise; Decision-Making; Systems

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INTRODUCTION

To say the least, artificial intelligence (AI) is developing with extraordinary speed. ChatGPT, an AI chatbot developed by OpenAI, is the fastest growing online service in history (Ahuja, 2023). The implications of AI for behavioral science may be particularly significant, extending far beyond the historic connection (Simon, 1981). Modern AI excels at pattern detection, from identifying animals within images to predicting text from an initial prompt. Modern behavioral science, particularly over the past 15 years, has focused on identifying and operationalizing bias and noise in human decision-making, and to providing correctives to reduce the effects of each (Hallsworth, 2023; Hallsworth and Kirkman, 2020; Halpern, 2015; Kahneman, 2011; Kahneman, Sibony and Sunstein, 2021; Thaler and Sunstein, 2008). Bias and noise are, essentially, behavioral patterns. Thus, AI is likely to be valuable within behavioral science for modelling and examining human behavior and perhaps for improving it, or improving on it (Mills, 2022a; Ludwig andMullainathan, 2022). For that reason, the use of AI alongside behavioral science is likely to be widespread in many applicable domains, such as consumer research and public policy (Sunstein, 2023).

This article outlines some opportunities and costs of AI-based behavioral science, including algorithmic behavioral science, in the coming years.

We highlight important work already done to identify discriminatory biases, such as racist and sexist word associations (*d-biases*), within natural language text via AI methods (Bolukbasi *et al.*, 2016; Brunet *et al.* 2019; Caliskan *et al.*, 2017). At the same time, we note that relatively little work (Horton, 2023; Jones and Steinhardt, 2022) to date has used AI to identify cognitive biases (*c-biases*), which are the focus of modern behavioral science. This is a clear, immediate opportunityfor AI in behavioral science research (Ludwig and Mullainathan, 2022, 2021; Mills, 2023; Sunstein, 2022a, 2022b, 2019).

Modern behavioral science has also received significant criticism in recent years (Chater and Loewenstein, 2022; Maier *et al.*, 2022), some of it highlighting the need for more contextualized behavioral approaches that incorporate heterogeneity (Hallsworth, 2023a, 2022; Hecht *et al.*, 2022; Mills, 2022b, 2021;

Schimmelpfennig and Muthukrishna, 2023; Sunstein, 2023; Szaszi *et al.*,2022). This 'heterogeneity revolution,' (Bryan, Tipton and Yeager, 2021) is likely to be promoted and accelerated by AI technologies (Agrawal *et al.*, 2022; Michie *et al.*, 2017; Mills, 2022a; Rauthmann, 2020), both as a new tool for behavioral science and in conjunction with existingstrategies, such as mega studies (Buyalskaya *et al.*, 2023; Duckworth and Milkman, 2022; Milkman*et al.*, 2022; Milkman *et al.*, 2021).

Finally, from a complex systems perspective, AI has the potential to help behavioral scientists to 'see the system' (Hallsworth, 2023b). This may be through predicting the optimal timing and context for delivery of interventions (Mills, 2022c; Yeung, 2017). It may also take the form of probing human behavior as a complex system to identify optimal leverage points for affecting behavior change (Hallsworth, 2023b; Park *et al.*, 2023; Schmidt and Stenger, 2021).

AI also creates new costs for practitioners and consumers. We briefly address the environmental effects of AI in behavioral science (Crawford, 2021; Dhar, 2020; Wu *et al.*, 2022). Where behavioral science uses AI in behavioral interventions to promote pro-environmental consumer behaviors, these energy-intensive methods must factor into the final evaluation of the intervention. However, environmental costs will affect all disciplines that use AI. As such, we focus more on costs specific to behavioral science practitioners and consumers.

AI-behavioral models may impose substantial social costs, as by endangering privacy through data collection (Hagendorff, 2022; Sætra, 2020; Saheb, 2022), and interfering with the formationof individual preferences (Bommasani *et al.*, 2022; Russell, 2019; Sunstein, 2022a). The latter risk is particularly important when considering vulnerable individuals, such as children (Akgun and Greenhow, 2022; Smith and de Villiers-Botha, 2021). At least with regulation of various kinds, AI may be limited in its ability to accommodate important individual and societal values, and that limitation may undermine public trust and produce welfare costs from interventions otherwise forgone (Mills, 2023). Finally, AI-behavioral approaches may not be economically viable in somedomains where existing behavioral science methods are appropriate (Mills, 2022b; Sunstein, 2023, 2012). Furthermore, skill premiums are likely to be high for professionals who command effective knowledge of behavioral science and AI, meaning that – at least in the near-term – establishedmethods may prove more economically viable (Hallsworth, 2023b; Lipton and Steinhardt, 2018).

Understanding the opportunities of behavioral science and AI, as well as these costs, will be crucial for determining best-practice applications, and regulatory policy to protect consumers and citizens.

OPPORTUNITY 1: IDENTIFYING BIASES

While behavioral science uses a suite of tools to affect behavior change (Hallsworth, 2023b,2022), and points to the need to go beyond merely identifying 'flaws' in human behavior (Bryan, Tipton and Yeager, 2021; Gigerenzer, 2018; Nisa *et al.*, 2020; Schimmelpfennig and Muthukrishna,2022), identifying bias and noise with AI is a clear opportunity for behavioral science. Behavioral biases can be understood as predictable patterns or error in human behavior (Kahneman, 2011; Thaler and Sunstein, 2008, 2003; Tversky and Kahneman, 1974), and the pattern-detecting capabilities of modern AI are likely to be well-suited to the task of identifying biases from behavioral data (Kleinberg *et al.*, 2018; Kleinberg *et al.*, 2015; Ludwig and Mullainathan, 2022, 2021; Mills, 2023; Sunstein, 2022a, 2022b, 2019). In fact, AI may identify biases that have never been identified before (Ludwig and Mullainathan, 2022). Equally, noise may hide patterns in behavior that humans may fail to spot, but that AI can identify and quantify (Aonghusa and Michie, 2020).

AI has been used to identify discriminatory biases within human behavior. For instance, *Word2Vec* is a natural language processing AI developed by Google (Mikolov *et al.*, 2013). Like many natural language AI systems, *Word2Vec* identifies the statistical relationships between wordsin terms of probabilities and uses these relationships to identify word associations (Wolfram, 2023).A user can then explore these associations through posing questions to the AI. Through such questioning, *Word2Vec* has often been found to produce gender-biased word associations (Bolukbasi *et al.*, 2016; Brunet *et al.* 2019). 'Word embedding' models such as *Word2Vec* have also been used as 'Word Embedding Association Tests' (WEATs) to replicate the results of the Implicit Associations Test (IAT) using only (big) text data (Caliskan *et al.*, 2017; Evenepoel, 2022). In both instances, only natural language is used to identified various discriminatory biases, and thus it is not that the AI systems themselves are biased, but rather, that AI can be used to identify implicitbiases in natural language that were previously hidden (Brunet *et al.*, 2019).

These results suggest several opportunities. Such approaches represent alternatives approaches to, say, the IAT, for investigating human behavior. Methods such as the IAT can be challenging to implement and time-consuming (and raise questions about external validity). Furthermore, AI approaches can unlock new avenues for behavioral research. For instance, the WEAT can beapplied to any corpus of natural language data and can thus be used to explore implicit biases across different cultural groups and time periods (Evenepoel, 2022). One need not focus on language; the potential is much broader. AI pattern detection has been used to investigate the decision-making processes of judges and doctors, with practices such as 'mugshot bias' (the tendency to rely heavily on a defendant's mugshot) identified through AI analysis (Kleinberg *et al.*,2019; Kleinberg *et al.*, 2018; Ludwig and Mullainathan, 2022, 2021; Sunstein, 2022a).

We are speaking here of discriminatory biases, or d-biases. While such biases have a long association with behavioral science, they are distinct from the cognitive biases (Wilke and Mata, 2012) – or c-biases – which generally concern modern behavioral science (Sunstein, 2022b). Thisis important to note to distinguish discussions of AI for detecting biases in behavioral science from the extensive literature on algorithmic bias (which generally focuses on d-biases). Relatively little work to date has explored the use of AI to identify c-biases (Horton, 2023; Jones and Steinhardt, 2022), though importantly, some AI-based analyses have shown judges (Kleinberg *et al.*, 2018; Ludwig and Mullainathan, 2022) and doctors (Mullainathan and Obermeyer, 2022) to use more prominent information in a manner which is indictive of availability bias and representativeness bias (Mills, 2023; Sunstein, 2022b). AI techniques have also been used to study habit formation behavior within especially large datasets, identifying important factors that influence consumption habit formation, which may have been difficult to determine via traditional statistical techniques (Milkman *et al.*, 2023).

The relative paucity of such work should be seen as a compelling opportunity for research within behavioral science. Indeed, it is hardly premature to speculate about the possibilities such a research programme might hold. For instance, real-time data on the behavior of a financial stock trader – such as the status of their portfolio, the speed of their mouse clicks, the frequency of their email communications, and so on – might be used to predict whether the broker is in a 'hot' state, and automatically trigger risk management procedures ranging from nudge-like interventions (e.g.,"you should take a break from the desk") to more coercive interventions (e.g., imposition of temporary trading limits).

OPPORTUNITY 2: INTEGRATING HETEROGENEITY

Beyond expanding the toolkit by which researchers investigate human behavior, AI presents a unique opportunity for behavioral science to progress in a way that meets various concerns about the field.

Recent high-profile results have sparked considerable debate (Hallsworth, 2023a, 2022). In particular, questions have been raised about the effectiveness of some behavioral interventions(Maier *et al.*, 2022), given what are often small effect sizes (Beshears and Kosowsky, 2020; DellaVigna and Linos, 2022; van der Linden and Goldberg, 2020). Concern has also been raised about the value of behavioral interventions that are focused on individual behavior (Chater and Loewenstein, 2022), given current policy challenges such as climate change (Bergquist *et al.*, 2023;Nisa *et al.*, 2020). These concerns supplement earlier concerns about certain uses of behavioral insights in public policy, which have been challenged for potentially undermining individual autonomy and freedom of choice (Gigerenzer, 2015; Henderson, 2014; Mitchell, 2005; Rebonato, 2014, 2012; Rizzo and Whitman, 2020, 2009; Ryan, 2018; Sugden, 2013, 2009; Veetil, 2011).

These different concerns – of being insufficiently effective and disrespectful to individuals – may or may not have force, and may be addressed by better integrating individual heterogeneity and context into behavioral science (Bryan, Tipton and Yeager, 2021; Hallsworth, 2023a, 2023b, 2022;Hecht *et al.*, 2022; Mills, 2022b, 2021; Schimmelpfennig and Muthukrishna, 2023; Sunstein, 2023;Szaszi *et al.*, 2022). The effectiveness of behavioral interventions is likely to depend on a multitude of factors, from the precise tool chosen (a default role, a warning, a reminder, a tax, a subsidy, amandate; Sunstein, 2023), to individual traits (Mills, 2022b; Peer *et al.*, 2020; Thunström *et al.*, 2018), to strength of preferences (de Ridder, Kroese and van Gestel, 2022) to cultural factors (Schimmelpfennig and Muthukrishna, 2023).

In recent years, behavioral studies have increasingly used moderation and mediation approaches to probe behavioral results to find and identify heterogeneous effects within a sample (Dolgopolova *et al.*, 2021; Hecht *et al.*, 2022; Jachimowicz *et al.*, 2019; Nekmat, 2020; Peer *et al.*,2020; Thunström *et al.*, 2018) – for instance, when evaluating calorie labels (Thunström, 2019) or COVID-19 interventions (Kantorowicz-Reznichenko *et al.*, 2022; Krpan *et al.*, 2021). This can lead to a deeper understanding of the factors influencing the intervention, and thus creates opportunities for interventions to be tailored to specific environments, individuals, or policy objectives (Agrawal *et al.*, 2022; Mills, 2022b; Sunstein, 2023). More tailored interventions may also empower individuals to 'self-nudge,' reassured that such interventions are attuned to their personalpreferences and objectives (Krpan and Urbaník, 2021).

While such approaches are promising, and interject much needed nuance into the evaluation of behavioral results (Bryan, Tipton and Yeager, 2021; Hallsworth, 2022; Szaszi *et al.*, 2022), approaches such as analyzing the potential moderators of behavioral interventions are limited by the potentially subjective choices in how the sample is stratified to investigate the effect of, say,gender or personality. Furthermore, examining all possible combinations of heterogeneous factors on an identified effect may be too resource-intensive given current research practices, as moderators themselves may be moderated by additional factors. Indeed, for n variables being examined, an approximate estimate for the number of potential models – without prior theory –would be *n!*, or *n*-factorial (Hayes, 2013). The question of resource intensity is particularly pertinent as behavioral science research increasingly uses 'mega studies' to investigate interventions (Duckworth and Milkman, 2022). These studies represent a very different route to understanding heterogeneous effects by embracing the power of scale. But in doing so, they are also burdenedby huge amounts of data, creating an opportunity for AI to assist in the analysis (Matz *et al.*, 2017; Milkman *et al.¸* 2023).

AI may reduce or resolve many of the challenges brought by the added complexity of heterogeneity analysis (Lazer *et al.*, 2009). Deep learning AI systems, which dominate current AI modelling, may accommodate an essentially unlimited number of input variables in an *n*-length input vector. For instance, rather than examining the effect of extraversion on a consumer behavior, and *separately* examining the effect of openness on that same behavior, an AI approach would allow each consumer's unique personality profile to be examined holistically, leading to a predictive AI modelthat integrates far more heterogeneity than moderation approaches can accommodate (Kosinski *et al.*, 2013; Kosinki *et al.*, 2015; Matz *et al.*, 2017). These individual-level variables are likely to be accompanied by various other contextual variables, such as time of day or location (Benartzi, 2017;Hauser *et al.*, 2014; Hauser *et al.*, 2009; Milkman *et al.¸* 2023), to further integrate heterogeneous factors, as many 'autonomous choice architects' already do (Hermann, 2021; Hui *et al.*, 2021; Johnson, 2021; Mills, 2022a, 2022c; Mills and Sætra, 2022; Morozovaite, 2021; Yeung, 2017).

Heterogeneity-respecting behavioral interventions, developed through AI, may lead to more effective (Mills, 2022b) and equitable (Sunstein, 2023) interventions that simultaneously address concerns about the effect size of interventions given the scale of some policy challenges (Chaterand Loewenstein, 2022; Nisa *et al.*, 2020). At the same time, a new-found emphasis on context andheterogeneity may turn out to be a sufficient response to the concern that behavioral interventions are homogeneous, one-size-fits-all strategies (Hallsworth, 2022). Interesting results are already being found. For instance, AI recommendation algorithms to personalize reading recommendations for children, accounting for their abilities and tastes, have been found to produce higher levels of reading (Agrawal *et al.*, 2022).

OPPORTUNITY 3: HANDLING COMPLEXITY

AI invites applied behavioral science to embrace, where relevant, the complexity inherent in real human behavior, and points towards an understanding of behavior as part of a complex adaptive system (Hallsworth, 2023b). In some of its forms, behavioral science has several overlaps with the fields of complexity economics (Bickley and Torgler, 2021; Foster, 2006; Rosser and Rosser, 2015; Sanbonmatsu *et al.*, 2021; Sanbonmatsu and Johnston, 2019; Simon, 1981; Spencer, 2018), which uses computational techniques to model the behavior of many artificial agents within economic systems (Arthur, 2021), and cybernetics (DeYoung, 2015; Forrester, 1971), which examines how information and feedback drive the evolution of simple and complex systems (Beer,2002).

Behavioral interventions do not exist outside of the environment in which behavior occurs (Banerjee and Mitra, 2023; Sanders, Snijders and Hallsworth, 2018), and furthermore, behavior is typically not a static exercise, but a continuous one, with behaviors occurring before and after any intervention (Dolan and Galizzi, 2015; Galizzi and Whitmarsh, 2019; Krpan, Galizzi and Dolan, 2019; Maki *et al.*, 2019; Nafziger, 2020). An opportunity for AI within behavioral science is therefore predicting the optimal environments, including time of intervention delivery and before/after spillover effects of interventions (Michie *et al.*, 2017; Mills, 2022c). For instance, generative AI may be used to model many artificial agents within an 'artificial society,' to investigate behavioral responses to an intervention within a computer 'sandbox,' prior to real-world implementation (Aher *et al.*, 2023; Argyle *et al.*, 2023; Park *et al.*, 2023). This perspective requires behavior to be viewed not as a homogeneous, individual state, but as a dynamic, adaptive response to environmental factors (Hallsworth, 2023b; Sapolsky, 2017).

Complexity and cybernetic perspectives encourage one to understand behavior as part of a wider system where different 'variables' within the system all represent potential opportunities to intervene and affect behavior change (Beer, 1993, 1979, 1970; Forrester, 1971). Particularly important variables within systems have been dubbed 'leverage points,' (Abson *et al.*, 2017; Leventon, Abson and Lang, 2021; Riechers *et al.*, 2021; Schmidt and Stenger, 2021). Within acomplex system, these variables have an outsized effect on the system as a whole, and from a behavioral perspective, have been offered as a valuable direction for future research to understand how behavioral interventions can be targeted to produce substantial behavior change (Abson *et al.*, 2017; Hallsworth, 2023b; Schmidt and Stenger, 2021; West *et al.*, 2020).

Identifying such points, however, may be difficult owing to the complexity of the system. Large amounts of data are required to appropriately model a sufficiently complex system (Beer, 1993;Komaki *et al.*, 2021; Meadows, 1997; Simon, 1981). Furthermore, these systems – by their nature – tend to be difficult to reduce to effective, useable models for sustained periods of time, leading to what systems theorists have dubbed the 'dancing with systems' problem (Meadows, 2001).

AI represents a promising approach for mapping behavioral systems and identifying leverage points (Ng, 2016), which in turn may enhance the effectiveness of behavioral interventions (Hallsworth, 2023b; Sanders, Snijders and Hallsworth, 2018; Schmidt and Stenger, 2021). Again, this is due to the dual technological advantages of AI in analyzing large amounts of data, and dynamically detecting patterns in data. As behavioral science develops to tackle more complex behavioral challenges, there will be a growing need for strategies to understand complexity, and design interventions capable of responding to and leveraging such complexity effectively. AI may facilitate the interjection of more complexity into this ever more interdisciplinary field.

COSTS

AI will create several costs for behavioral science practitioners, and consumers. Some costs, such as the environmental cost of building, using, and maintaining massive AI systems, are costs that all disciplines that embrace AI technologies must address (Crawford, 2021; Dhar, 2020; Wu *et al.*, 2022). For instance, the carbon cost of training an AI model for a study of publication quality has been estimated to be the equivalent of the carbon consumption of approximately two average American lifetimes, or seven average global lifetimes (Hao, 2019; Strubell *et al.*, 2018). Where, say, AI-behavioral models are used to design and implement behavioral interventions to promotepro-environmental consumption decisions, the energy cost of such models must be a factor in the overall policy assessment, changing the required effectiveness of the behavioral intervention to compensate for the deleterious effects of developing and delivering it (Mills and Whittle, 2023).

Consumers and citizens might also face costs of diverse kinds; some of them are difficult to quantify. These include costs that arise from data collection, in terms of privacy costs (Hagendorff,2022; Sætra, 2020; Saheb, 2022), and from implementation, in terms of experiential costs (Russell,2019; Sunstein, 2022a; Tanner, 2021) such as outcome homogenization (Bommasani *et al.*, 2022). For instance, where sensitive data are required for an AI-behavioral model to effectively function, but the rationale for using such data cannot be explained to the data subject – perhaps due to alack of theoretical underpinning (Forde and Paganini, 2019; Gibney, 2018) – there is an ever- present risk that data is being misused and privacy unjustifiably violated. Even if justifiable, thepotential benefits of AI-behavioral models, in terms of predictive capacity and welfare-enhancing behavioral interventions, should not be taken as sufficient to assume consent for data collection (Sætra, 2019). Such social costs are particularly pronounced when considering vulnerable individuals, such as children, and the potential harms that AI-behavioral models may induce through intervening to change behavior at times of critical cognitive and personal development (Akgun and Greenhow, 2022; Russell, 2019; Smith and de Villiers-Botha, 2021).

There is also a pervasive risk of manipulation (Sunstein, 2015). AI might be used to lead people in directions that are not in their interest, perhaps by exploiting a lack of information or behavioral biases (Bar-Gill *et al.*, 2023). Indeed, pattern detection abilities could enable AI not only to personalize in a way that promotes people's welfare, but also to use their biases to their detriment. The costs along these dimensions could be high.

It is important, from a policy perspective, to retain human oversight and accountability for any costs that are incurred (Mills and Sætra, 2022). Having some 'human in the loop' is recognized in emerging AI position papers, such as in the UK (UK Centre for Data Ethics and Innovation, 2020), and is supported by research into public attitudes concerning algorithmic influence (Aoki, 2021; Ingrams *et al.*, 2021; Peppin, 2022; Kozyreva *et al.*, 2021).

While one may wish to balance social costs against the estimated welfare outcomes of more accurate or personalized interventions (Sunstein, 2012), poor theoretical underpinnings of AI-behavioral models may lead to a reliance on large datasets containing potentially sensitive behavioral details, lest the accuracy of the models be undermined. Broadly, the costs of AI- behavioral models, and the enhanced accuracy such approaches might bring (Mills, 2022b; Sunstein, 2023) should be weighed against the social and welfare costs of more generic, but less data-invasive, approaches to behavior change. For the foregoing reasons, AI-driven approaches may be less economical than established behavioral science approaches. While contextualizing interventions and using heterogeneity analysis to respect individual autonomy are substantial opportunities, it is important to recognize that behavioral science has already contributed much to public life without using such technologies (Beshears and Kosowsky, 2020; Jachimowicz *et al.*, 2019; Sanders, Snijders and Hallsworth, 2018). Where existing behavioral science competencies can deliver adequate benefits, an AI-behavioral approach may ultimately be more costly, in both time and economic costs. The cost of skills may also be a factor. As some have argued in computer science (Lipton and Steinhardt, 2018), the lack of skilled AI researcher capacity has led to limited critical oversight in AI development, with the costs of resolving this issue tied to the economic cost of enhancing skills. While emerging fields, such as behavioral data science, appear promising, there is likely to be a persistent skill premium which keeps the costs of AI-behavioral approaches high compared to established techniques, at least in the near-term.

This highlights an important additional risk: rapid deployment of AI-behavioral models is likely to demand more in terms of skills than present capacity within behavioral science can meet (Hallsworth, 2023b), which in turn creates the possibility of mis-deployment and misuse (Mills, 2023). Patience in the development of this space, coupled with efforts to build capacity and understand the necessary safeguards for AI-behavioral models – given the potential costs involved – is likely critical to the successful implementation of AI within behavioral science, and to the development of appropriate policy guidance and consumer protections.

CONCLUSION

The opportunities AI presents for behavioral science are significant. AI has promise as a means of probing human behavioral data to identify new cognitive biases, or to identify known cognitive biases in novel contexts. AI may also promote the 'heterogeneity revolution' in behavioral science by allowing significantly more data to be used in the design and implementation of behavioral interventions. From a complex systems perspective, AI may be well-suited for optimizing the timing and context of intervention delivery, again enhancing effectiveness, as well as probing behavioral systems as a whole to predict optimal leverage points for affecting behavioral change.

AI usage in behavioral science will also create costs. As with all disciplines, behavioral science must synthesize the environmental costs of energy-intensive AI technologies into its practice. To those behavioral interventions that seek to promote pro-environmental behaviors, such a cost is particularly pertinent. AI will also create various social costs for consumers and citizens, which behavioral science must face. These include privacy costs from collecting potentially sensitive data on individual behavior, and the risks of AI-behavioral models interfering with vulnerable individuals. There are also several economic costs. AI-behavioral models are likely to raise the skill-requirements of behavioral science practitioners, making these approaches more expensive. Where such skills are scarce, there is also the risk that such methods are used without adequateunderstanding or oversight, leading to misuses and welfare costs suffered by the public. Furthermore, behavioral science can already do much without AI methods, and existing competencies should always be considered in comparison to potentially more costly alternatives.

As AI technologies develop, their potential will inevitably grow. The most productive paths forward focus on the distinctive opportunities and costs of an AI-driven behavioral science, with particular emphasis on the opportunity to learn more than ever before about both bias and noise,and to use what is learned to increase human welfare.

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CHAPTER 7

GENERAL DISCUSSION[1]

In the ever-evolving landscape of industrial safety, the concept of nudging emerges as a promising force for change. The evaluation of its potential has been the main objective and central tenet of this doctoral thesis. The idea is simple but profound: by understanding human behavior and cognitive processes, we can design interventions that gently guide individuals toward safer choices (Thaler & Sunstein, 2008). This departure from traditional safety measures, such as training and protocols, opens new doors to surpass the stagnating safety improvements that industrial safety management faces today (Lindhout & Reniers, 2017).

This discussion delves into the intricacies of nudging for industrial safety, exploring the application of behavioral science to mitigate risks. We start with insights on social influence from the COVID-19 study and its implications for industrial safety. Followed by a discussion of all safety nudges tested throughout the chapters, their effectiveness in promoting safety behavior and the strategic nudge development; using Münscher et al. (2016) taxonomy of choice architecture. Further, we address the long-term effectiveness and scalability of the tested safety nudges, and explore the concept of 'layered nudging'.

Furthermore, the discussion clarifies how dual-process theories of decision-making (incl. system 1 and 2, Kahneman (2011)) provide a new psychological framework for industrial safety, and the importance a holistic safety approach, integrating multiple behavioral, procedural and technical interventions, to maximize its impact. Lastly, we extend beyond nudging by emphasizing the relevance

[1] Partially based on Costa, S., Mills, S., Soman, D., Duyck, W., & Dirix, N. (2023). *Advancing Applied Behavioral Science: The GAP Framework.* [Manuscript in preparation]

of other behavioral tools (e.g., behavioral audits) that leverage the features of bounded rationality (Dhami & Sunstein, 2022), and by indicating how recent developments in artificial intelligence (AI) can advance applied behavior science (Mills, Costa, et al., 2023). The aim here is to highlight the potential of adopting bounded rationality as a behavioral lens when developing behavior change initiatives to enhance industrial safety.

In a world where safety is a top priority, this discussion paves the way for a deeper understanding of how nudging and applied behavioral science can revolutionize industrial safety practices and foster an environment of well-being and protection. An endeavor that, in my opinion, we owe to all employees and families involved.

NUDGING HAND HYGIENE AND THE RELEVANCE FOR INDUSTRIAL SAFETY

The COVID-19 pandemic presented an unprecedented challenge to societies worldwide (Daniel, 2020; Delardas et al., 2022; Ray et al., 2021). In CHAPTER 2, we discussed an experiment applying the principles of nudging to encourage adherence to COVID-19 protective guidelines. A central insight emerging from this study pertains to the effectiveness of nudges in fostering hand hygiene. Nudges addressing factors like reducing friction, enhancing salience, and leveraging social norms proved highly successful in encouraging hand sanitization; confirming the findings of nudge studies in more health or hygiene related contexts (e.g., hospitals, schools and supermarkets) (Goff, 2022; Van Dessel et al., 2022). These findings underscore the significance of designing choice architecture to guide behavior effectively, which is especially important in times of global crisis and uncertainty (Van Bavel et al., 2020).

This study goes beyond individual behavior and delves into the intriguing dynamics of group influence and herd behavior (Banerjee, 1992; Cialdini & Goldstein, 2004). It reveals that people passing by in groups are more likely to sanitize their hands compared to individuals, and that this effect is largely mediated by the behavior of the first person in the group. This underscores a classic example of herd behavior, where individuals in a group conform to the actions of their peers, believing that the lead person possesses information or insiht they lack, or because their fear of social disapproval drives them to conformity (Asch, 1956). These insights on social influence are highly relevant to the realm of industrial safety given the large weight modern safety management places on safety culture and leadership (DeJoy, 2005; Vierendeels et al., 2018). In organizational settings, the behavior of one employee can influence the actions of others, leading to a sort of contagion or 'bandwagon effect' (Schmitt-Beck, 2015). This suggests that strategically targeting the 'first movers', for example individuals in (informal) influential positions or just the first person in a group, can amplify the impact of nudge interventions. By understanding and harnessing these social dynamics, organizations can create a ripple effect that encourages safety compliance throughout the workforce (Fugas et al., 2011), thus significantly enhancing overall safety measures. In CHAPTER 5, we saw that social proof nudges were able to promote the use of the safe pathways by visually displaying the number of colleagues that used the path before them. This example shows how nudges can also leverage social influence to foster industrial safety behaviors, and most likely the associated perceptions and values (i.e., via peer influence) that form the pillars of a broader safety culture (DeJoy, 2005).

In the following section, we provide a more comprehensive overview of the different nudges tested to promote industrial safety and its implications.

THE EFFECTIVENESS OF NUDGES PROMOTING INDUSTRIAL SAFETY BEHAVIOR

Nudging holds promise as a complementary approach to conventional safety measures, such as training and rule enforcement that rely more on deliberate thought (Lindhout & Reniers, 2017). By leveraging insights from behavioral science, safety experts can design nudging interventions that align with the cognitive processes and decision-making tendencies of the workers, taking both subliminal influences and cognitive constraints into consideration (Kahneman, 2011; Love et al., 2023).

The study discussed in CHAPTER 3, conducted two field experiments and found that cost-effective nudges can encourage safety behaviors in the domains of gas hazards and staircase safety (or broader 'working at height'). These nudges included reminders in the form of hand-shaped cues to hold handrails, gas icon reminders on work attire to ensure gas detector compliance, and commitment strategies with social reference points. Notably, the most effective nudges were those that were consistently present in the workplace, such as the gas icon and hand-shaped stickers. This suggests that for sustained industrial safety behaviors, continuous exposure to nudges is crucial, which is not surprising given the complex nature of safety actions that often require often repeated decisions throughout the day, instead of just one. In addition, by making safety more visible and present through nudges, one could foster the idea among workers that managers put more effort into safety (Vierendeels et al., 2018). This perception in turn might lead to reciprocal tendencies of workers (Molm et al., 2007), proven to be an important factor in safety management (DeJoy, 2005) making them more willing to comply to safety guidelines (Walker & Hutton, 2006) and potentially more receptive to further safety nudges.

In CHAPTER 4, we found both reminders and feedback nudges to be effective in promoting safety communication practices in the workplace, namely by increasing both the frequency and the spread of safety talks performed by the supervisors and middle management. The personal feedback nudge proved the most effective. This aligns with the literature highlighting that personalization, and contextualization, can increase the impact of nudge interventions (Milkman et al., 2021; Mills, 2022). These findings also indicate that safety nudges prove useful for multiple industrial target audiences, including workers with specific characteristics (e.g., level of education and personality traits, see Damen et al. (2023) and Tasdelen and Özpinar (2023)), as well as individuals in supervisory roles with different cognitive and emotional profiles (Metzler & Bellingrath, 2017) and a more diverse gender representation (i.e., more women) (Padavic, 1992).

In CHAPTER 5, the study underscores effective nudge interventions to enhance industrial safety, focusing on maintaining safe distances from suspended loads. It used three approaches: social proof to promote the usage of safe pathways, reducing friction to foster the use of no-touch tools, and salient light projection beneath loads to increase awareness and keeping distance. All of these interventions reached large effect sizes, which is not unique but still uncommon for nudging (DellaVigna & Linos, 2022), and seemed to be complementary with more standard safety measures (e.g., new no-touch tools). Essentially, these findings display how important and contagious peer safety behavior can be (Newaz et al., 2019), and how relevant it is to instrumentalize it by making good examples more visible (Bicchieri, 2017; Cialdini, 2021). Further, they highlight the power of simple principles, such as the required effort and salience of the desired safety actions. When developing floor plans of new industrial factories and workplaces, typically done from a more practical and rational perspective, attention should be paid to adequate placement of safety equipment. This aligns with the idea of 'choice infrastructure' (i.e., adequate human design from the start) as opposed to choice architecture that is most often used to overcome problems resulting from inadequate (human) design (Hallsworth, 2023). In addition, the effective salient light projection shows how simple visible cues, that address system 1 more directly, can make passersby more aware of potential danger and nudge appropriate action. This has the advantage that in cognitive demanding situations, common for industrial settings (e.g., fatigue, temperatures, loud noise and time pressure; cfr. 'cognitive load', Sweller (1988)), workers are still being nudged to safety, while system 2 depending processes (e.g., actively monitoring every risk) might run out of fuel, fail and fall back on system 1 (Kahneman (2011)). Aligning with the results of our mobile eye-tracking experiment.

When implementing nudges it remains important to consider ethical implications. The use of nudging raised ethical concerns due to its potential to influence behavior without explicit consent (Lin et al., 2017). Critics argue that nudging may compromise autonomy and operate on paternalistic grounds (Hansen & Jespersen, 2013). However, proponents, such as Sunstein (2015), contend that the influence of choice architecture is inevitable, and objections should focus on specific nudges rather than the concept as a whole. Ethical frameworks like FORGOOD offer dimensions like fairness, openness, and respect, and guidance for ethical conduct (Lades & Delaney, 2022). In the context of workplace safety, and consistently applied in our studies, the collaboration with safety experts, unions and the participants themselves (in varying degrees) is advised to ensure ethical appropriateness and to monitor that the interest of all stakeholders are guarded at all times.

One of the key takeaways from this thesis is the recognition that safety behavior is not solely determined by motivation and knowledge, but is deeply influenced by subtle cognitive processes (also see Love et al. (2023)). These results are a promising first step showing the potential benefits of safety nudges and their success in addressing the more subtle psychological influences. Nonetheless, the question remains how nudge effects evolve over time; a critical factor that will be addressed in the following section.

THE PERSISTENCY OF NUDGE EFFECTS OVER TIME

The long-term effectiveness of nudges is a lacuna in the literature to date, with most studies traditionally focusing on their short-term impact (Beshears & Kosowsky, 2020). What became clear is that the sustainability of nudge effects over time depends on factors such as the specific nudge type used and the context in which they are applied (Brandon et al., 2017; Van Rookhuijzen et al., 2021). To establish nudges as an integral part of safety management, comprehensive longitudinal analyses are crucial (Krause et al., 1999).

In CHAPTER 4, we discussed the most comprehensive longitudinal study evaluating safety nudge effects over a period of 1.5 years. This study aimed evaluated the potential of nudges to promote the number and the spread of safety talks among the workforce, which has proven to be an effective way to promote overall safety (Olson et al., 2016; Rice et al., 2022). Recall that the aim here was to influence the behavior of supervisors directly and worker behavior indirectly (cfr. 'nudge the nudger', Dudley and Xie (2022); House et al. (2022)). In Experiment 1, different nudges had varying positive impacts on the frequency of perfomed safety talks in different departments. Personalized feedback nudges were more effective, aligning with previous research (Mills, 2022b). Importantly, post-tests revealed here that continued nudge presence was crucial to maintain positive behavior change and that the learning effect after a short implementation period (i.e., 1 month) was limited to non-existing. The personal feedback nudge in experiment 2 proved its ability to increase the spread of talks significantly among the workforce over a remarkable extended period of 1.5 years (and counting). The effect knew a slight decrease, but remained largely intact, and therefore provides a highly valuable argument to integrate the nudging approach in both organizational and governmental behavior change strategies (Benartzi et al., 2017; Soman & Yeung, 2020). Note that while these long-term effects are promising, as well as those of the other experiments with effects lasting up to 3 to 6 months, further research still has to explore what type of (safety) nudges and contextual moderators contribute to long-term success.

As we delve into the nuances of nudging for industrial safety, it becomes clear that a deeper understanding of the cognitive mechanisms is essential and that a strategic approach is needed. The following section provides a clear overview of dominant psychological constraints that influence all daily decision-making, including safety decisions, and a matched categorization of nudge interventions that can inform systematic and strategic nudge development.

STRATEGIC NUDGING: A TAXONOMY OF CHOICE ARCHITECTURE

Münscher et al.'s (2016) taxonomy of choice architecture provides a strategically valuable framework for designing nudging interventions. This taxonomy, comprising three clusters — Decision Information (DI), Decision Structure (DS) and Decision Assistance (DA) — that are built around distinct psychological barriers, offers a structured approach to develop effective nudge strategies. The three psychological barriers involved include the limited access to decision information (DI), limited capacity to compare choice options and the related tendency to minimize effort (DS) and limited attention and self-control (DA).

While Münscher et al.'s (2016) classification is not all encompassing, we argue that it is one of the best and most practical in the wide range of frameworks that exist today. For example, the overview provided by Beshears and Kosowsky (2020) of nudge research include overlapping and vague categories (e.g., 'nudges that trigger system 1', 'by harnessing biases'). Similar for the overview of Hummel and Maedche (2019) that mainly aims to summarize nudging research and not classify the underlying psychological principles of the behavioral techniques. Frameworks like MINDSPACE (Dolan et al., 2010) on the other hand, list the most common nudging techniques, but do not offer guidance under which broader categories they fall or what behavioral principles (or targeted barriers) they have in common. Münscher et al.'s (2016) nudge taxonomy does provide a useful theoretical framework with high practical value, but continuous updates are necessary to accommodate ever new and harder to classify behavioral techniques (e.g., priming).

Integrating Münscher et al.'s (2016) taxonomy with a human factor categorization, which identifies and categorizes relevant human factors underlying accidents (Reason, 2000; Shappell & Wiegmann, 2001), creates a powerful synergy. This combined approach guides the development of nudges that are grounded in an understanding of cognitive and behavioral challenges in a given safety context (e.g., unintended incidents due to forgetting should be targeted with DA interventions, such as reminders, as opposed to, for example, DI techniques such as social norm messages). This approach emerged as strategic implementation method from this doctoral thesis and has been integrated in the operations of the Belgian steel plant since to operationalize the proven nudge potential. Future assessment (in 1 or 2 years) will have to investigate if this approach enables a broader enhanced safety performance of the organization, extending beyond the successful results of the discussed field experiments.

Using a standard method, including a comprehensive nudging taxonomy, offers a structured path for safety managers to ensure that nudge interventions are systematically designed, implemented, and evaluated. This systematic approach enhances the transparency and replicability of nudge strategies, a critical consideration in the realm of behavioral science (Bryan et al., 2021; Ruggeri et al., 2020), but even more relevant for nudging in industrial safety. While safety interventions that fall under the definition of 'a nudge' exist (e.g., yellow tread edge highlighters, Foster et al. (2014)), they do not follow a systematic approach or widely accepted taxonomy. This however, is necessary to transfer relevant findings to new contexts and to gradually build a range of proven behavior techniques and scalable applications (Hallsworth, 2023).

In the following section, we go deeper on how safety nudges can be integrated in multiple layers of an organization and how multiple nudges combined tend to have a bigger effect; which is promising given common critics on typically smaller nudge effects.

LAYERED NUDGING

When developing industrial safety nudges, it is important to incorporate established insights from the most recent safety models on human error and human factors (Lindhout & Reniers, 2017). In CHAPTERS 4 and 5, we discussed renowned safety models that show the complex interplay of factors leading to an accident, including Reasons' Swiss Cheese Model (Perneger, 2005; Reason, 1990; Reason,

2000) and the HFACS model developed from it (Shappell & Wiegmann, 2001; Wiegmann & Shappell, 2001). The Swiss Cheese model populated the idea that safety exist out of multiple layers and that accidents only occur because of flaws in every layer. Implementing and improving multiple lines of defense (e.g., better organization, supervision or training), therefore, should be able to prevent accidents in different stages, from early contributing organizational factors (e.g., insufficient safety resources) to direct leading factors on the work floor itself (e.g., distraction).

By transferring this lines-of-defense reasoning to nudge applications, we proposed the new concept of 'layered nudging'. In the horizontal approach, multiple nudges target different aspects of behavior on the same 'layer' (e.g., 'flawed organizational decisions', 'unsafe supervision' and 'unsafe acts'; cfr. HFACS) simultaneously or in rapid succession. Conversely, the vertical layered approach involves a sequence of nudges targeting multiple layers (i.e., multiple agents in the hierarchy), each building on the previous one to guide individuals towards a desired behavior.

Layered nudging's innovative aspect lies in its incorporation of various nudges across different levels and capitalizes on the additive (or multiplicative) effects of nudges that are commonly found in the literature (Ayal et al., 2021; Brandon et al., 2019). Also in our experiments, we found combined nudges to have nearly always a bigger effect than their individual implementations (e.g., the combination of gas icons with push buttons or salient footsteps and social norm messages exerting a bigger influence). In CHAPTER 5, we nudged multiple aspects that relate to hazardous exposure to suspended loads (i.e., on the same horizontal 'unsafe acts' layer), but had to test it in different departments and locations, not allowing to measure the aggregate effect of all nudge interventions combined. Further research should aim to assess these aggregate effects (both horizontal and vertical), as this approach is likely to maximize the nudging potential and can counter frequent criticism of the typical small effect sizes of nudge interventions (DellaVigna & Linos, 2022; Maier et al., 2022). Important will be to identify which nudge techniques influence which individuals in what way (i.e., a heterogeneous approach, Bryan et al. (2021)) and potential reverse effects on others (i.e., distributional effects, Sunstein, 2022a). Additionally, one should carefully asses which combined techniques, targeting different psychological mechanisms (or barriers), contribute to the biggest additive effect (e.g., memory lapse + intention, intention + effort, all three, etc.).

Layered nudging holds the potential to create a more comprehensive and impactful behavioral shift than solitary interventions, and could equally facilitate culture change initiatives (e.g., nudge more safe behaviors, make them more visible and communicate changing social norms to employees). It further emphasizes the role nudging can play for industrial safety and makes the question more pertinent how the practice of nudging and dual-process theories can serve as an innovative perspective on modern safety management. The following section aims to elucidate how both concepts form the pillars of a new psychological paradigm to evaluate and alter industrial safety behavior.

A NEW PSYCHOLOGICAL FRAMEWORK AND HOLISTIC SAFETY APPROACH

Examples of behavioral nudges in the field of industrial safety exist by definition (e.g., visual signage or auditory signals), but the strategic incorporation of nudging into this domain has been lagging (Lindhout & Reniers, 2017). Likewise, dual-process theories of decision-making have not yet been adopted by the industrial safety literature, but could serve as a new psychological framework to understand the intricate complexities of safety behavior. Those frameworks can define and clarify the role of more profound, and often subliminal, psychological influences and help to structure not only the development of nudges, but behavior change programs at large (Mazar & Soman, 2022). Hallsworth (2023) suggests using the insights in bounded rationality as a "behavioral lens" to view human behavior and to match the efforts to change it accordingly.

Kahneman's (2011) metaphorical system 1 and 2 have proven valuable in defining psychological mechanisms underlying successful nudges in variety of domains (Hansen & Jespersen, 2013). Similar for industrial safety, referring to both systems and proven categorization of nudging techniques (Münscher et al., 2016) are likely to enhance the communication and systematical evaluation (Maier et al., 2022; Mertens et al., 2022) of (successful) behavioral approaches and to foster continuous improvement in this field. Following more recent advancements in the domain of traffic safety (Avineri, 2014). This new 'behavioral lens' should not only be used to evaluate and counter unsafe acts of workers, but also to monitor the biased decision-making of top executives, and all agents in between that can impact safety performance indirectly (Molnar et al., 2019; Schorn, 2023). Targeting this high-level decision-making, while highly impactful, is often overlooked in behavior change initiatives (Dudley & Xie, 2022). In general, recognizing cognitive limitations can guide the development of interventions that are better aligned with human cognition and its primal drivers, instead of forcing behavior change through external rewards, punishment and enforcement, which historically has been the go-to strategy (Hofmann et al., 2017), and should be done systematically throughout the whole organization's operations (i.e., from top to bottom).

Further, it is important to recognize that system 2 interventions, such as work instructions, training, monetary incentives and safety talks remain crucial for effective safety management (Spigener et al., 2022). Nudges, while valuable, are not standalone solutions for complex safety challenges. They serve as tools to complement modern safety management, which heavily relies on human decision-making, but should be integrated in a broader holistic safety approach. Such an approach develops interventions that ideally address (boundedly rational) human, technical, and organizational elements in symbiosis. In CHAPTER 5, we found a holistic approach, combining nudges (e.g., placement) with more standard safety measures (e.g., new tools, participation), to be very effective in promoting the usage of no-touch tools (i.e., going from 5 to 84% and persisting up to 6 months). While further experimentation is needed, we argue that such combined approaches should serve as the golden standard for behavior change initiatives in industrial safety.

The main objective of this doctoral thesis was to assess the potential of safety nudges in an industrial production environment. In the following section, we reflect on how emerging innovations, such as behavioral audits and AI, can advance the field of applied behavioral science (incl. nudging) and how these innovations are relevant to industrial safety.

ADVANCING APPLIED BEHAVIORAL SCIENCE

Among the myriad techniques in applied behavioral science, nudging gained prominence as a cost-effective means to elicit behavioral change (Benartzi et al., 2017; Thaler & Sunstein, 2008), providing novel ways to steer individual choices and behavior in desired directions. However, while valuable, nudging represents just one facet of the multifaceted toolbox of behavioral science (Schmidt & Stenger, 2021). As applied behavioral science matures, a more holistic approach that goes beyond nudging is needed. In this section, we cover emerging areas in this field to identify and counter flawed decision-making, such as algorithms and behavioral audits, discuss their opportunities and address practical considerations (incl. costs and ethics). For each area, reflections are made about its relevance for industrial safety.

Algorithms

Where human judgement is prone to biases and noise (i.e., non-systematic distortion of decision-making, for example by moods), algorithms – broadly defined as predefined computational rules - represent promising tools to support decision-making (Kahneman et al., 2021). When trained on diverse datasets, some algorithms can reduce cognitive biases and reduce noisy variability, in comparison to human decision-making (Sunstein, 2023). For instance, Kleinberg et al. (2017) find algorithms to predict reoffending rates better than human judges using the same data available at the time of the hearing. As discussed in CHAPTER 6, the advent of AI, or 'advanced algorithms', offers both opportunities and challenges in the realm of behavioral science and nudging. AI can play a pivotal role in behavioral analysis by detecting patterns in behavioral data, offering insights into decision-making processes, and identifying opportunities for targeted interventions. We propose three main ways how AI can advance applied behavioral science.

Firstly, AI revolutionizes data collection by automating the gathering of extensive datasets, including text and sentiment analysis (Babu & Kanaga, 2021; Michie et al., 2017). This broadens the range of data sources for studying human behavior, facilitating megastudies that compare interventions in the same population (Milkman et al., 2021). Handling massive datasets is made efficient through AI, enabling streamlined data exploration (Tyler et al., 2023; Wang et al., 2023).

Secondly, AI is crucial for data analysis, identifying behavioral patterns and addressing anomalies in decision-making processes, such as bias and noise (Mills, Costa, et al., 2023). It can differentiate between areas where human expertise enhances outcomes from those where bias outweighs expertise (Kahneman et al., 2021). Enhanced pattern detection equally includes understanding habit formation (Buyalskaya et al., 2023), crucial for safety (Björgvinsson & Wilde, 1996; De Pelsmacker & Janssens, 2007), and constructing complex behavioral networks (Fung et al., 2023), guiding interventions for substantive change.

Thirdly, AI enhances efficiency by automating behavior change strategies with varying levels of human supervision, potentially outperforming human intervention (Dwivedi et al., 2021; Jarrahi, 2018). AI systems can serve as autonomous choice architects (Mills & Sætra, 2022), automating test-retest trials and adjusting interventions in real time, a concept referred to as 'hypernudging' (Mills, 2022a). While this raises ethical concerns, it has the potential to accelerate research and interventions, especially for important societal challenges, including (occupational) safety (Pishgar et al., 2021).

In the context of industrial safety, AI's data collection and synthesis capabilities can provide a wealth of information for safety analysis (Forcina & Falcone, 2021), while its enhanced identification features can help identify patterns, anomalies, and potential safety hazards in complex operational environments. Additionally, the efficiency gains achieved through AI automation can streamline safety processes and provide real-time insights for better decision-making (Jeske et al., 2021), such as personalized feedback (Mills, 2022b), contributing to a safer industrial setting. Overall, AI is a powerful tool in the behavioral scientist's and safety expert's arsenal, supporting efforts to scale interventions and overcome persistent challenges. While most suggestions in the safety literature for AI to improve safety management (i.e., 'industry 4.0', Lasi et al. (2014)) maintain a more rational perspective, thus mainly enhancing standard safety measures (Liu et al., 2020), our suggestions support how AI can assist safety from a boundedly rational perspective as well.

However, the adoption of AI in behavioral science is not without costs. Energy and environmental considerations are paramount, as AI algorithms require significant computational resources (Dhar, 2020). Moreover, the fast-paced evolution of AI applications, including those leveraging subliminal influences (e.g., hypernudging, Mills (2022a)), makes ethical considerations and safeguards, such as sufficient regulations, more pertinent (Mills, Costa, et al., 2023). Similarly, privacy concerns and compliance with GDPR must be carefully managed when using AI to collect and analyze behavioral data (Ryan, 2020). Striking a balance between the benefits and costs of AI in behavioral science is essential for ethical and sustainable research and practice.

Behavioral audits

In recent years, nudging has been paired with auditing techniques to reveal unwanted friction (or 'sludge') (Sunstein, 2022b), cognitive biases (Fang et al., 2019), and noise (Kahneman et al., 2021). These 'behavioral audits' emerged to systematically assess the underlying drivers of behavior and decision-making within organizations, aiming to align practices with desired and more just outcomes. These auditing techniques enable to screen and identify flawed decision-making that impact safety on all organizational layers (cfr. layered nudging and HFACS), and help to overcome them by providing the fundamental basis for choice architectural adaptations, as well as other counter measures, such revised (decision) procedures and sensibilisation (Mills, 2023).

Sludge audits entail a systematic examination of bureaucratic processes with the goal of eliminating unnecessary complexities, redundancies, and barriers that burden individuals and businesses (Sunstein, 2022b). They enhance operational efficiency by streamlining procedures, reducing paperwork, and improving user-friendliness. Sludge audits contribute to cost savings, productivity gains, and increased transparency and accountability (Mills, Whittle, et al., 2023).

Bias audits systematically review an organization's policies and decision-making to uncover implicit and explicit biases. These audits can, for example, promote fairness and inclusivity, addressing discriminatory practices through data analysis, surveys, interviews, and benchmarking against industry standards (Emerson & Lehman, 2022; Fang et al., 2019). Recently, bias audits have been proposed as a vital element of algorithmic design (Morewedge et al., 2023), as such an algorithmic audit revealed how e-commercial recommender algorithms (e.g., Facebook) trained on intuitive (newsfeed content consumed) as opposed to more-deliberative user behavior (friended people) to exhibit more out-group bias (Lee & Hosanagar, 2019). Bias audits serve as a tool for behavioral change, advocating awareness, choice architectural adaptations, policy revisions, and ongoing monitoring.

Noise audits methodically examine factors introducing variability into decision-making processes (Kahneman et al., 2021). Noise, stemming from personal mood, cognitive biases, and inconsistent rule application, leads to unpredictable outcomes (Bonavia & Marin-Garcia, 2023). Kahneman et al. (2021) indicate that reducing noise involves establishing guidelines, providing training, algorithmic automation (which they state is by default 'noise free'), feedback, checklists, and continuous monitoring, ensuring consistency and decision accuracy.

Safety audits are crucial and have become a vital aspect of evaluating and improving (industrial) safety performance in the last decades (Birkmire et al., 2007; Spellman, 2020). When adopting the new boundedly rational perspective, the aforementioned behavioral audits should be integrated in (and informed by) currently established safety auditing procedures to maximize their impact; aligning with the idea of a more holistic safety approach. These behavioral audits can help identify and rectify biases, streamline processes, and reduce variability (i.e., noise), ultimately enhancing safety measures and ensuring more consistent, informed decision-making in industrial settings (Love et al., 2023). The enhanced transparency and accountability also bolsters safety practices by minimizing errors and delays in critical safety procedures (Love & Matthews, 2022). In addition, these audits can assist in identifying organizational weak spots (e.g., flawed basic assumptions) that prevent successful culture change initiatives (DeJoy, 2005; Guldenmund, 2000; Murata, 2017).

Costa et al. (2023) suggest a unified behavioral auditing program would be valuable to account for bounded rationally, as current practices remain fragmented, concentrating on specific behavioral phenomena like sludge, bias, and noise. Further research, including theoretical work, is needed to elaborate on an integrated behavioral auditing framework, but its potential is promising. In the following section, we outline some future guidelines to advance behaviorally informed safety management.

GUIDELINES FOR FURTHER RESEARCH

While this thesis is the first to systematically examine and confirm the potential of nudging in enhancing industrial safety, there is much more to explore. Future research should aim to refine interventions based on the evidence presented here, building on behavioral techniques that proved successful in these initial experiments (e.g., social norms, alteration of friction, salience, priming and feedback formats). Additionally, investigating contextual moderating factors is crucial to advance applied behavioral interventions, and remains one of the biggest challenges today (C. Bryan et al., 2021). Understanding how factors such as organizational culture (Kubera, 2023), worker demographics (Sunstein, 2022a), personality traits (Beus et al., 2015) and industry-specific features (e.g., extreme temperatures, dirty environments, night shifts, etc.), impact the success of nudges can inform targeted safety interventions and enhance scalability (Hallsworth, 2023). Furthermore, the potential of layered nudging approaches, both horizontal and vertical ones, should be explored as a promising complementary element of a holistic safety approach (incl. potential spillovers effects, Van Rookhuijzen et al. (2021)). Important here, is to not only explore the combination of nudges, but also the aggregate effect together with more standard safety measures, and assess the evolution of the effect over time. Our findings support the long-term potential of nudges, which is highly valuable given the gap in the literature (Beshears & Kosowsky, 2020), but further long-term assessment is needed to support nudging as a new established safety tool (Krause et al., 1999).

Field experiments in diverse industrial contexts are essential to assess the transferability of nudging strategies, but also face methodological challenges associated with real-world applications (Samek, 2019). Further research in laboratory or online contexts could elaborate on testing specific variations (e.g., priming effects of different colors and symbols in safety settings or slightly adjusted framing of messages), distilling the most active components of successful aggregated nudge interventions, that would require too many resources in applied industrial settings (i.e., scarce similar control locations and costly observation methods). Those more controlled testing environments have to compromise on ecological validity, but compensate this with a higher internal validity that neatly complements applied methodological challenges (Privitera, 2022). Similar to a holistic safety approach, a versatile range of methods is needed to explore the full potential of bounded rationality as a new perspective on industrial safety management (Costa et al., 2023; Lindhout & Reniers, 2017). This includes massive collaborative efforts, such as megastudies (Milkman et al., 2021), that can assess if the effect of safety nudges and the occurrence of associated cognitive biases holds in diverse cultures and countries world-wide (Ruggeri et al., 2019); which has at times shown to differ (e.g., conceptual color associations differing among Chinese and English people, Tham et al. (2020)).

In the broader landscape of behavioral science, it is essential to address limitations and chart future directions. The lack of clear nudge definitions and theoretical frameworks presents a challenge to researchers and practitioners (Saghai, 2013). A unified comprehensive framework that consolidates existing knowledge and provides a clear vision for the future of nudging is needed (Lin et al., 2017). Some endeavors are promising, such as the recent inference nudging framework (Van Dessel et al., 2022), integrating goal-directed inferential processes underlying behavior impacted by nudges, and the choice architectural framework of Münscher et al. (2016), that encompasses clusters of nudging techniques built around distinct psychological mechanisms. Further research should aim to replicate (inference nudging perspective), extend (taxonomy Münscher) and integrate these, and other new, theoretical frameworks to foster more successful nudge applications.

Moreover, behavioral science extends beyond nudging alone. Recognizing its broader potential and the capacity to address the boundedly rational individual is essential to ensure advancement in all applied settings, including industrial safety. Research should extend its focus to address bias and noise in decision-making more broadly (e.g., via behavioral audits) and adopt a systems-level view of behavior in industrial settings (Chater & Loewenstein, 2022). Novel technologies, such as AI, can assist in providing insights in complex causal networks, identify (new) biases and automate behavioral interventions, and should therefore be embraced by both researchers and practitioners (Mills, Costa, et al., 2023). However, it is crucial that sufficient ethical safe guards are in place to minimize the impact of (un)intended harm (Ryan, 2020). While these ethical considerations can impose a challenge, they also provide an opportunity for behavioral scientists, as experts in the field, to provide advice on installing these safe guards (e.g., inoculation strategies to counter the influence of misinformation, Van Der Linden (2023)).

CONCLUSION

This doctoral thesis has illuminated the transformative potential of a new boundedly rational perspective and nudging in enhancing safety behavior within industrial settings. From nudging adherence to COVID-19 guidelines to its integration into holistic safety approaches, the journey has been one of discovery and promise. Layered nudging appeared as a promising approach, combining established safety models with the practice of nudging that proved successful in a series of field experiments. Some of these safety nudges maintained their effect up to 1.5 years later, contributing to the sparse literature on long-term nudge effectiveness. By outlining future perspectives, it is clear that the best is yet to come, as researchers and practitioners continue to refine, expand, and innovate within the realms of applied behavioral science, with high practical value for industrial safety. Key recommendations entail including boundedly rational behavioral perspectives in safety auditing (incl. bias, noise and sludge) and embracing innovative AI methods, while putting sufficient ethical safeguards in place. In general, the findings confirm the nudge potential for industrial safety and highlight that the path forward is illuminated by new insights and frontiers, with each step bringing us closer to a safer, more informed, and more (boundedly) rational future.

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CHAPTER 8

ENGLISH SUMMARY

In the dynamic landscape of heavy production industries safety stands as a critical pillar. While industrial safety has made substantial strides, recent advancements seem to have hit a plateau (Hudson, 2007). A significant revelation is that up to 90% of accidents trace back to human errors, highlighting the imperative for a more profound comprehension of safety behavior (Kletz, 2001). This thesis undertakes a comprehensive exploration, unraveling the historical foundations of industrial safety, addressing the existing impasse in safety innovation, and proposing a transformative trajectory through the lens of behavioral science (Lindhout & Reniers, 2017; Love et al., 2023). Key focal points include dual-process decision-making theories and the strategic application of nudging, which is systematically evaluated through a series of field experiments in the steel industry. Responding to challenges imposed by the COVID-19 pandemic, we started the thesis with an exploration on how behavioral insights can counter the spread of infectious viral diseases in an industrial plant. Responding to opportunities enabled by the recent AI revolution, we ended by clarifying promising avenues for applied behavioral science when adopting cutting-edge machine learning innovations. This thesis, therefore, provides an encompassing overview of the potential of a new boundedly rational perspective on health and safety management in industrial production environments.

In CHAPTER 2, we explored the potential of nudges to control the spread of infectious viruses during the COVID-19 pandemic. More specifically, this study investigated how hand hygiene compliance can be nudged in a private company environment where health and hygiene are less prevalent, addressing a gap in the literature (Goff, 2022). The research focused on three behavioral change techniques: reducing friction, enhancing salience, and leveraging social norms. Strategically placing hand sanitizers and incorporating visual cues and social norm messages, proved successful in influencing individuals' hand sanitizing behavior. Moreover, combining these interventions produced a cumulative effect, emphasizing the additivity of nudges. Importantly, group dynamics seemed to play a significant role. Our results revealed that people in groups are more likely to adopt hand hygiene practices and that this group effect is mediated by the behavior of the first person in the group.

In CHAPTER 3, we discussed the first field study to systematically investigate the nudge potential for industrial safety (Lindhout & Reniers, 2017). Our results revealed that small and cost-efficient nudges can effectively promote safety behavior related to gas detector compliance and staircase safety. The results emphasize the effectiveness of omnipresent nudges in the workplace, such as gas icons and hand-shaped stickers. It aligns with the idea that continuous exposure to nudges is crucial for influencing enduring safety behavior, aiming to target multiple recurring decision moments that might be more complex than trying to influence one decision (e.g., to enroll in a pension-saving program, Thaler and Benartzi (2004)). In this chapter, we introduce bounded rationality and dual-process theories as a new psychological framework for addressing industrial safety behavior, and clarify how this aligns with the suggested nudging approach; implemented strategically via the choice architecture taxonomy of Münscher et al. (2016).

In CHAPTER 4, we evaluated nudges aiming to counter fallible supervisory behavior and assessed how their effect evolves over time, addressing a persistent gap in the literature (Beshears & Kosowsky, 2020). The findings from two experiments reveal positive effects of feedback nudges, both social and personal feedback, on the frequency and spread among the workforce of safety talks. Experiment 1 showed that the presence of nudges played a crucial role in sustaining the desired behavior change, here performing more safety talks. This suggests the need for ongoing or extended nudge presence, and thus a limited learning effect. Experiment 2 revealed that the feedback nudge targeting the spread of safety talks largely persisted over a long period of 1.5 years, with a slight decrease over time. We conclude that strategic nudge development has the potential to become part of a holistic safety approach, however, further assessment of the long-term effects of nudge interventions and moderating contextual influences is needed.

In CHAPTER 5, we investigated nudging strategies' effectiveness in enhancing safety practices related to heavy suspended loads. Three experiments involving social proof, friction, and salience nudges demonstrated that these interventions effectively increased the distance workers maintained from suspended loads. Experiment 1, involving social proof, showed that displaying the number of colleagues using safe routes encouraged others to do the same. Experiment 2, altering friction, revealed that placing no-touch tools nearby was more effective than instructions from supervisors. A holistic approach here, also including participation of employees and new tools, led to a large increase in compliance rates and is proposed as golden standard for behavior change initiatives. The salience study found that projecting a light under suspended loads significantly encouraged workers to maintain a safe distance. Layered nudging emerged as a new valuable concept that integrates horizontal (multiple nudges at once) and vertical strategies (sequential nudges across different organizational levels) for greater impact.

In CHAPTER 6, we provided guidance on how recent development in AI can advance the field of behavioral science, which is highly relevant for all applied settings aiming to address flawed decision-making, including industrial safety. We highlighted three main opportunities. The first includes leveraging AI's pattern detection capabilities to identify previously unidentified and known biases in different contexts. A second opportunity involves tailoring and contextualizing behavioral interventions to maximize their impact, aligning with the proclaimed necessary heterogeneity approach (Bryan et al., 2021). Thirdly, AI can aid behavioral scientists in understanding complex and evolving models of human behavior by providing tools to visualize and analyze these dynamics. Apart from the advantages, we also discussed potential costs, including environmental, economic and ethical challenges.

The studies presented in this doctoral thesis provide an answer to multiple gaps in both the behavioral science as safety literature. First, they pioneer the idea of adopting bounded rationality as new psychological framework for industrial safety management and are the first to systematically evaluate and confirm the associated potential of nudge interventions. Secondly, our findings provide evidence that nudge interventions can hold their effect over long extended periods (i.e., up to 1.5 years), be it with a slight decrease, as long as they remain present (i.e., limited learning effects). Thirdly, we provide a response to frequent nudge critics, concerning smaller effect sizes, by showing nudge effect often add up, and provide a promising avenue to leverage this feature by adopting a new layered nudging approach. This layered nudging approach further highlights the relevance of nudging for safety, given it originated from a symbiosis with established and dominant safety models (i.e., the Swiss Cheese Model and HFACS). Finally, we advance the field of applied behavioral science in general by proposing and clarifying promising new avenues, such as behavioral auditing (incl. bias, noise and sludge) and innovative machine learning opportunities. This while highlighting the importance to keep ethical safeguards in place and the opportunity of behavioral audits to control for harmful influences (incl. in algorithm design, Morewedge et al. (2023)).

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CHAPTER 9

NEDERLANDSTALIGE SAMENVATTING

In het dynamische landschap van zware productie-industrieën is veiligheid een cruciale pijler. Hoewel de industriële veiligheid aanzienlijke vooruitgang heeft geboekt, lijken recente ontwikkelingen een plateau te hebben bereikt (Hudson 2007). Een belangrijke ontdekking is dat tot 90% van de ongevallen te herleiden zijn naar menselijke fouten, wat het belang onderstreept van een dieper begrip van veiligheidsgedrag (Kletz 2001). Deze scriptie onderneemt een uitgebreide verkenningstocht waarbij de historische evolutie van industriële veiligheid wordt toegelicht, de bestaande impasse in veiligheidsinnovatie wordt aangepakt en een transformerende koers wordt voorgesteld door de lens van de gedragswetenschap (Lindhout & Reniers 2017; Love et al. 2023). Belangrijke aandachtspunten zijn tweeledige beslissingstheorieën en de strategische toepassing van nudging, die systematisch wordt geëvalueerd door middel van een reeks veldexperimenten in de staalindustrie. Als reactie op uitdagingen opgelegd door de COVID-19 pandemie, begonnen we de scriptie met een verkenning van hoe gedragsinzichten kunnen helpen bij het tegengaan van de verspreiding van besmettelijke virale ziektes in een industriële omgeving. Reagerend op mogelijkheden geboden door de recente AI-revolutie, eindigden we met het verduidelijken van veelbelovende wegen voor toegepaste gedragswetenschap bij het aannemen van geavanceerde 'machine learning'-innovaties. Deze scriptie biedt dus een allesomvattend overzicht van het potentieel van een nieuw begrensd rationeel perspectief op gezondheids- en veiligheidsmanagment in een industriële productieomgeving.

In HOOFDSTUK 2 hebben we het potentieel van nudges onderzocht om de verspreiding van besmettelijke virussen tijdens de COVID-19 pandemie te beheersen. Specifieker onderzocht deze studie hoe de naleving van handhygiëne in een bedrijfsomgeving, waar gezondheid en hygiëne minder prevalent zijn, genudged kan worden, waarmee een lacune in de literatuur wordt aangepakt (Goff 2022). Het onderzoek richtte zich op drie technieken voor gedragsverandering: het verminderen van weerstand ('friction'), het vergroten van de opvallendheid ('salience') en het benutten van sociale normen. Het strategisch plaatsen van handdesinfecterend middel en het integreren van visuele signalen en boodschappen over sociale normen bleken succesvol in het beïnvloeden van het handontsmettingsgedrag van individuen. Bovendien leidde de combinatie van deze interventies tot een cumulatief effect, waarbij de additiviteit van nudges werd benadrukt. Belangrijk is dat groepsdynamiek een cruciale rol speelt. Onze resultaten tonen aan dat mensen in groep eerder geneigd zijn handhygiënepraktijken over te nemen en dat dit groepseffect wordt gemedieerd door het gedrag van de eerste persoon in de groep.

In HOOFDSTUK 3 bespraken we de eerste veldstudie die systematisch het nudge-potentieel voor industriële veiligheid onderzocht (Lindhout & Reniers 2017). Onze resultaten toonden aan dat kleine en kostenefficiënte nudges effectief veiligheidsgedrag kunnen bevorderen, met name met betrekking tot het dragen van gasdetectoren en veiligheid op trappen. De resultaten benadrukken de effectiviteit van sterk aanwezige nudges op de werkplek, zoals gasiconen en stickers in de vorm van handen. Dit stemt overeen met het idee dat voortdurende blootstelling aan nudges cruciaal is voor het beïnvloeden van duurzaam veiligheidsgedrag, gericht op het beïnvloeden van meerdere terugkerende beslissingsmomenten wat mogelijk complexer is dan het beïnvloeden van slechts één beslissing (e.g., om deel te nemen aan een pensioenspaarprogramma, Thaler en Benartzi (2004)). In dit hoofdstuk introduceren we begrensde rationaliteit en tweeledige beslissingstheorieën als een nieuw psychologisch kader voor het aanpakken van industrieël veiligheidsgedrag en verduidelijken we hoe dit aansluit bij de voorgestelde nudging-aanpak, strategisch geïmplementeerd via de keuzearchitectuur taxonomie van Münscher et al. (2016).

In HOOFDSTUK 4 hebben we nudges geëvalueerd die gericht zijn op het corrigeren van feilbaar superviserend gedrag en bekeken hoe hun effect zich over de tijd heen ontwikkelt. Zo komen we tegemoet aan een aanhoudende leemte in de literatuur (Beshears & Kosowsky 2020). De bevindingen uit twee experimenten onthullen positieve effecten van feedback nudges, zowel sociale als persoonlijke feedback, op de frequentie en verspreiding van veiligheidsgesprekken onder de werkkrachten. Experiment 1 toonde aan dat de aanwezigheid van nudges een cruciale rol speelde bij het in stand houden van de gewenste gedragsverandering, in dit geval het vaker uitvoeren van veiligheidsgesprekken, wat wijst op een behoefte aan de voortdurende aanwezigheid van nudges gezien slechts een beperkt leereffect gevonden werd (na wegname van de nudge). Experiment 2 onthulde dat het effect van de feedback nudge gericht op de verspreiding van veiligheidsgesprekken grotendeels bleef bestaan over een zeer lange periode van 1,5 jaar, met een lichte afname over tijd. We concluderen dat strategische nudge-ontwikkeling deel kan uitmaken van een holistische veiligheidsaanpak, maar dat verdere beoordeling van de langetermijneffecten van nudge-interventies en modererende contextuele invloeden nodig is.

In HOOFDSTUK 5 hebben we de effectiviteit van nudging-strategieën onderzocht om veiligheidspraktijken met betrekking tot zware hangende lasten te verbeteren. Drie experimenten met betrekking tot sociale bewijsvoering ('social proof'), weerstand ('friction') en opvallendheid ('salience') toonden aan dat deze interventies effectief de afstand die werknemers houden van hangende lasten vergrootten. Experiment 1, gericht op sociale bewijsvoering, toonde aan dat het weergeven van het aantal collega's dat veilige routes gebruikt, anderen aanmoedigde hetzelfde te doen. Experiment 2, gericht op het wijzigen van weerstand, onthulde dat het dichtbij plaatsen van no-touch tools effectiever was dan instructies van leidinggevenden. Een holistische benadering, inclusief de betrokkenheid van medewerkers en nieuwe hulpmiddelen, leidde tot een grote toename in het gebruik van de tools en wordt voorgesteld als de gouden standaard voor gedragsveranderingsinitiatieven. De studie over opvallendheid ('salience') en gewaarwording vond dat het projecteren van een licht onder hangende lasten werknemers aanzienlijk aanmoedigde om een veilige afstand te bewaren. 'Layered nudging' (of gelaagde nudging) dook op als een nieuw waardevol concept dat horizontale (meerdere nudges tegelijk) en verticale strategieën (opeenvolgende nudges op verschillende organisatieniveaus) integreert voor een grotere impact.

In HOOFDSTUK 6 gaven we inzichten en richtlijnen over hoe recente ontwikkelingen in AI het veld van gedragswetenschappen kunnen bevorderen. Wat zeer relevant is voor alle toegepaste omgevingen die gericht zijn op het aanpakken van feilbare besluitvorming, inclusief industriële veiligheid. We benadrukten drie belangrijke mogelijkheden. De eerste omvat het benutten van AI's vermogen tot patroonherkenning om voorheen ongeïdentificeerde en bekende 'biases' (of systematische denkfouten) in verschillende contexten te identificeren. Een tweede kans omvat het op maat maken en contextualiseren van gedragsinterventies om hun impact te maximaliseren, in lijn met de noodzakelijke meer heterogene aanpak in de gedragswetenschap (Bryan et al. 2021). Ten derde kan AI gedragswetenschappers helpen bij het begrijpen van complexe en evoluerende modellen van menselijk gedrag door middel van tools om deze dynamiek te visualiseren en te analyseren. Naast de voordelen bespraken we ook potentiële kosten, waaronder milieu-, economische en ethische uitdagingen.

De in deze scriptie gepresenteerde studies bieden antwoorden op meerdere lacunes in zowel de gedragswetenschappen als de veiligheidsliteratuur. Ten eerste zijn ze baanbrekend in het idee van het toepassen van begrensde rationaliteit als een nieuw psychologisch kader voor industrieel veiligheidsmanagement en zijn ze de eerste die systematisch het bijbehorende potentieel van nudge-interventies evalueren en bevestigen. Ten tweede tonen onze bevindingen aan dat nudge-interventies hun effect over lange tijd kunnen behouden (tot 1,5 jaar), zij het met een lichte afname, zolang ze aanwezig blijven (dus met beperkte leereffecten). Ten derde bieden we een antwoord op frequente kritiek op nudges over kleinere effectgroottes door aan te tonen dat de effecten van nudges vaak additief zijn en layered nudging een veelbelovende weg biedt om deze eigenschap te benutten. Deze layered nudging-benadering benadrukt verder de relevantie van nudging voor veiligheid, aangezien het voortkomt uit een symbiose met gevestigde en dominante veiligheidsmodellen (e.g., het Swiss Cheese Model en HFACS). Tot slot bevorderen we het veld van de toegepaste gedragswetenschap in het algemeen door veelbelovende nieuwe wegen voor te stellen en te verduidelijken, zoals gedragsaudits (incl. bias, noise en sludge) en innovatieve machine learning-mogelijkheden. Dit terwijl we het belang benadrukken van het in stand houden van ethiek vrijwarende veiligheidsmaatregelen en de kans van gedragsaudits om voor schadelijke invloeden te controleren (incl. bij het ontwerpen van algoritmes, Morewedge et al. (2023)).

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APPENDIX 1A

Figure A1

The Golden Rules of Safety

APPENDIX 2A

Table A1

A detailed overview of the number of passersby and the alcohol gel consumption (in ml) per condition

Intervention	Passersby	Usage (in ml)	Usage (in ml/passerby)	Estimated compliance (in %)*
Control (pre-test)	12520	876	0.07	7%
Placement	9014	2434	0.27	27%
Placement-Footsteps	2393	1125	0.47	47%
Placement-Message	3075	1384	0.45	45%
Placement-Message-Footsteps	2830	1613	0.57	57%
Control (removal)	1300	117	0.09	9%
Total	31132			

Note. *Average user performing one push, which equals 1ml (see details in 'Observation method' section). Therefore, 'usage in ml' equals the expected number of users, and the 'usage in ml/passerby' equals the estimated compliance rate in %.

Table A2

A detailed overview of the number of passersby and hand sanitizer usage per condition (camera footage)

Intervention	Passersby	Usage	Usage (in %)
Control (pre-test)	6624	290	4.38%
Placement	4142	1141	27.55%
Placement-Footsteps	789	321	40.64%
Placement-Message	502	226	45.06%
Placement-Message-Footsteps	1938	987	50.91%
Control (removal)	650	36	5.54%
Total	14645		

APPENDIX 3A

Table A1

Structured observation form for tallying CO detector compliance (blank version and translated from Dutch)

Date: **Department:** Blast furnace and sinter plant **Observed team:**	**IMPORTANT:** ○ Only **workers**, no administrative employees passing by. ○ We do **not look if CO detectors are calibrated.** Reason: this requires addressing the workers, which can negatively affect the results of the research. ○ If workers are not okay or only partially okay, please **do not respond to them temporarily** (unless extremely necessary). This is detrimental to the study. We are looking at the effect of nudges on safety behavior. Not the effect of getting comments on safety behavior. ○ Please **tally** the numbers and enter this later in **Excel.**

Number of tallied workers in **total**	
How many workers:	
Wear a CO-detector	
Activated the CO detector	
Wear a CO-detector in the **right place** (activated or not) (right place = on the chest - uncovered)	
Wear a CO-detector in the **wrong place** (activated or not)	Beneath jacket
	On pants
	Somewhere else (specify where)
Are **completely compliant** (CO-detector activated + right place)	

APPENDIX 3B

Table B1

The number of pushes on the green and red buttons (Experiment 1)

Time	Green button	Red button
Day 1	198	95
Day 2	140	51
Day 3	115	40
Day 4	80	16
Day 5	120	28
Day 6	95	35
Day 7	151	27
Day 8	125	32
Day 9	109	28
Day 10	85	32
Day 11	120	20
Day 12	110	24
Day 13	123	49
Day 14	135	18
Day 15	82	30
Day 16	102	13
Day 17	130	25
Day 18	88	26
Day 19	125	35
Day 20	121	19
Day 21	101	35
Total	**2455**	**678**

APPENDIX 4A

Table A1

The evolution of the spread of safety talks for the control department 'GS'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	1.29**	1.03 - 1.63	*0.14*
Control (Apr 20)	1.24*	0.98 - 1.56	*0.12*
Control (June 20)	0.76**	0.60 - 0.97	*-0.15*
Control (July 20)	0.74**	0.58 - 0.94	*-0.17*
Control (Aug 20)	1.66***	1.32 - 2.09	*0.28*
Control (Sept 20)	1.97***	1.56 - 2.48	*0.37*
Control (Oct 20)	1.69***	1.34 - 2.13	*0.29*
Control (Nov 20)	1.27**	1.00 - 1.59	*0.13*
Control (Dec 20)	0.69***	0.54 - 0.88	*-0.21*
Control (Jan 21)	1.68***	1.34 - 2.12	*0.29*
Control (Feb 21)	2.42***	1.92 - 3.06	*0.49*
Control (Mar 21)	1.94***	1.54 - 2.44	*0.37*
Control (Apr 21)	1.90***	1.51 - 2.39	*0.35*
Feedback spread (May 21)	1.34**	1.06 - 1.68	*0.16*
Feedback spread (June 21)	2.02***	1.60 - 2.55	*0.39*
Feedback spread (July 21)	1.00	0.79 - 1.26	*0.00*
Feedback spread(Aug 21)	0.82*	0.65 - 1.03	*-0.11*
Feedback spread (Sept 21)	1.78***	1.41 - 2.26	*0.32*
Feedback spread (Oct 21)	2.12***	1.68 - 2.67	*0.41*
Feedback spread (Nov 21)	1.61***	1.28 - 2.03	*0.26*
Feedback spread (Dec 21)	1.23*	0.98 - 1.55	*0.12*
Feedback spread (Jan 22)	1.90***	1.51 - 2.39	*0.35*
Feedback spread (Feb 22)	1.81***	1.44 - 2.28	*0.33*
Feedback spread (Mar 22)	1.76***	1.40 - 2.20	*0.31*
Feedback spread (Apr 22)	1.37***	1.09 - 1.73	*0.18*
Feedback spread (May 22)	1.43***	1.14 - 1.8	*0.20*
Feedback spread (June 22)	1.52***	1.21 - 1.91	*0.23*
Feedback spread (July 22)	0.91	0.72 - 1.15	*-0.05*
Feedback spread (Aug 22)	0.90	0.71 - 1.14	*-0.06*
Feedback spread (Sept 22)	1.12	0.89 - 1.41	*0.06*
Feedback spread (Oct 22)	1.82***	1.45 - 2.30	*0.33*
Feedback spread (Nov 22)	1.03	0.82 - 1.30	*0.02*
Observations	19569		

Note. *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control (May 20)'

Table A2

The evolution of the spread of safety talks for the control department 'COO'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	0.63***	0.45 - 0.89	*-0.26*
Control (Apr 20)	1.02	0.72 - 1.43	*0.01*
Control (June 20)	0.77	0.55 - 1.09	*-0.14*
Control (July 20)	0.58***	0.41 - 0.81	*-0.30*
Control (Aug 20)	0.55***	0.39 - 0.78	*-0.33*
Control (Sept 20)	0.86	0.61 - 1.21	*-0.08*
Control (Oct 20)	1.13	0.80 - 1.6	*0.07*
Control (Nov 20)	0.93	0.66 - 1.31	*-0.04*
Control (Dec 20)	0.58***	0.41 - 0.81	*-0.30*
Control (Jan 21)	1.00	0.71 - 1.41	*0.00*
Control (Feb 21)	1.47**	1.03 - 2.10	*0.21*
Control (Mar 21)	2.13***	1.47 - 3.09	*0.42*
Control (Apr 21)	1.35*	0.95 - 1.92	*0.17*
Feedback spread (May 21)	1.29	0.91 - 1.83	*0.14*
Feedback spread (June 21)	1.50**	1.05 - 2.13	*0.22*
Feedback spread (July 21)	1.05	0.74 - 1.48	*0.03*
Feedback spread(Aug 21)	0.79	0.56 - 1.11	*-0.13*
Feedback spread (Sept 21)	0.89	0.63 - 1.25	*-0.07*
Feedback spread (Oct 21)	1.19	0.84 - 1.68	*0.10*
Feedback spread (Nov 21)	1.05	0.74 - 1.48	*0.03*
Feedback spread (Dec 21)	0.53***	0.37 - 0.74	*-0.35*
Feedback spread (Jan 22)	0.64**	0.46 - 0.90	*-0.25*
Feedback spread (Feb 22)	0.72*	0.51 - 1.01	*-0.18*
Feedback spread (Mar 22)	1.40*	0.98 - 1.99	*0.19*
Feedback spread (Apr 22)	0.93	0.66 - 1.31	*-0.04*
Feedback spread (May 22)	0.94	0.67 - 1.33	*-0.03*
Feedback spread (June 22)	0.53***	0.37 - 0.74	*-0.35*
Feedback spread (July 22)	0.50***	0.35 - 0.70	*-0.39*
Feedback spread (Aug 22)	0.60***	0.43 - 0.85	*-0.28*
Feedback spread (Sept 22)	0.45***	0.32 - 0.63	*-0.45*
Feedback spread (Oct 22)	0.67**	0.48 - 0.94	*-0.22*
Feedback spread (Nov 22)	0.73**	0.52 - 1.03	*-0.17*
Observations	8943		

Note. *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control (May 20)'

Table A3

The evolution of the spread of safety talks for the control department 'RM'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	0.94	0.71 - 1.25	*-0.04*
Control (Apr 20)	0.95	0.71 - 1.26	*-0.03*
Control (June 20)	0.70**	0.53 - 0.94	*-0.19*
Control (July 20)	0.71**	0.53 - 0.95	*-0.19*
Control (Aug 20)	0.52***	0.39 - 0.69	*-0.36*
Control (Sept 20)	0.73**	0.55 - 0.97	*-0.18*
Control (Oct 20)	0.74**	0.56 - 0.99	*-0.17*
Control (Nov 20)	0.73**	0.55 - 0.98	*-0.17*
Control (Dec 20)	0.66***	0.49 - 0.88	*-0.23*
Control (Jan 21)	0.78**	0.59 - 1.04	*-0.14*
Control (Feb 21)	1.89***	1.42 - 2.53	*0.35*
Control (Mar 21)	2.13***	1.59 - 2.85	*0.42*
Control (Apr 21)	1.65***	1.24 - 2.21	*0.28*
Feedback spread (May 21)	1.55***	1.16 - 2.06	*0.24*
Feedback spread (June 21)	1.53***	1.15 - 2.04	*0.24*
Feedback spread (July 21)	0.91	0.68 - 1.21	*-0.05*
Feedback spread(Aug 21)	0.99	0.75 - 1.32	*-0.01*
Feedback spread (Sept 21)	1.12	0.85 - 1.49	*0.06*
Feedback spread (Oct 21)	1.62***	1.21 - 2.16	*0.27*
Feedback spread (Nov 21)	0.95	0.71 - 1.26	*-0.03*
Feedback spread (Dec 21)	0.84	0.63 - 1.11	*-0.10*
Feedback spread (Jan 22)	1.3*	1.00 - 1.77	*0.16*
Feedback spread (Feb 22)	1.16	0.87 - 1.54	*0.08*
Feedback spread (Mar 22)	1.35**	1.01 - 1.79	*0.16*
Feedback spread (Apr 22)	1.17	0.88 - 1.56	*0.09*
Feedback spread (May 22)	1.04	0.79 - 1.39	*0.02*
Feedback spread (June 22)	0.84	0.64 - 1.12	*-0.09*
Feedback spread (July 22)	0.84	0.64 - 1.12	*-0.09*
Feedback spread (Aug 22)	0.62***	0.47 - 0.83	*-0.26*
Feedback spread (Sept 22)	0.73**	0.55 - 0.97	*-0.18*
Feedback spread (Oct 22)	0.73**	0.55 - 0.97	*-0.18*
Feedback spread (Nov 22)	0.78*	0.59 - 1.04	*-0.14*
Observations	12540		

Note. *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control (May 20)'

Table A4

The evolution of the spread of safety talks for the control department 'BF'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	1.24	0.93 - 1.66	*0.12*
Control (Apr 20)	1.12	0.84 - 1.49	*0.06*
Control (June 20)	0.87	0.65 - 1.16	*-0.08*
Control (July 20)	1.02	0.77 - 1.36	*0.01*
Control (Aug 20)	0.73**	0.55 - 0.97	*-0.17*
Control (Sept 20)	1.09	0.82 - 1.46	*0.05*
Control (Oct 20)	0.83	0.62 - 1.1	*-0.10*
Control (Nov 20)	0.75*	0.56 - 1.01	*-0.16*
Control (Dec 20)	0.75**	0.56 - 1.00	*-0.16*
Control (Jan 21)	0.94	0.70 - 1.25	*-0.04*
Control (Feb 21)	1.73***	1.29 - 2.32	*0.30*
Control (Mar 21)	1.86***	1.380 - 2.49	*0.34*
Control (Apr 21)	1.79***	1.33 - 2.40	*0.32*
Feedback spread (May 21)	1.56***	1.16 - 2.09	*0.24*
Feedback spread (June 21)	1.57***	1.17 - 2.11	*0.25*
Feedback spread (July 21)	1.31*	0.98 - 1.76	*0.15*
Feedback spread(Aug 21)	1.19	0.89 - 1.59	*0.10*
Feedback spread (Sept 21)	1.47**	1.10 - 1.97	*0.21*
Feedback spread (Oct 21)	2.29***	1.69 - 3.10	*0.46*
Feedback spread (Nov 21)	1.67***	1.24 - 2.24	*0.28*
Feedback spread (Dec 21)	1.34**	1.01 - 1.80	*0.16*
Feedback spread (Jan 22)	1.69***	1.26 - 2.26	*0.29*
Feedback spread (Feb 22)	1.81***	1.35 - 2.43	*0.33*
Feedback spread (Mar 22)	1.22	0.91 - 1.63	*0.11*
Feedback spread (Apr 22)	1.19	0.89 - 1.59	*0.10*
Feedback spread (May 22)	1.06	0.79 - 1.41	*0.03*
Feedback spread (June 22)	1.09	0.82 - 1.46	*0.05*
Feedback spread (July 22)	0.76*	0.57 - 1.02	*-0.15*
Feedback spread (Aug 22)	0.89	0.67 - 1.19	*-0.07*
Feedback spread (Sept 22)	1.65***	1.23 - 2.21	*0.28*
Feedback spread (Oct 22)	1.61***	1.20 - 2.16	*0.26*
Feedback spread (Nov 22)	1.41**	1.05 - 1.88	*0.19*
Observations	12177		

Note. *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control (May 20)'

Table A5

The evolution of the spread of safety talks for the control department 'CPM'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	0.78*	0.61 - 1.01	*-0.14*
Control (Apr 20)	1.18	0.92 - 1.51	*0.09*
Control (June 20)	0.77**	0.60 - 0.99	*-0.15*
Control (July 20)	0.71***	0.55 - 0.91	*-0.19*
Control (Aug 20)	1.02	0.79 - 1.30	*0.01*
Control (Sept 20)	1.41***	1.10 - 1.81	*0.19*
Control (Oct 20)	1.35**	1.05 - 1.73	*0.16*
Control (Nov 20)	1.06	0.83 - 1.36	*0.03*
Control (Dec 20)	0.63***	0.49 - 0.82	*-0.25*
Control (Jan 21)	1.87***	1.45 - 2.40	*0.34*
Control (Feb 21)	3.41***	2.62 - 4.45	*0.68*
Control (Mar 21)	2.91***	2.24 - 3.78	*0.59*
Control (Apr 21)	1.93***	1.50 - 2.48	*0.36*
Feedback spread (May 21)	2.10***	1.63 - 2.71	*0.41*
Feedback spread (June 21)	1.87***	1.45 - 2.40	*0.34*
Feedback spread (July 21)	0.98	0.76 - 1.25	*-0.01*
Feedback spread(Aug 21)	1.01	0.79 - 1.29	*0.00*
Feedback spread (Sept 21)	1.19	0.93 - 1.53	*0.10*
Feedback spread (Oct 21)	1.73***	1.35 - 2.23	*0.30*
Feedback spread (Nov 21)	1.68***	1.31 - 2.15	*0.29*
Feedback spread (Dec 21)	1.18	0.92 - 1.51	*0.09*
Feedback spread (Jan 22)	2.12***	1.65 - 2.73	*0.41*
Feedback spread (Feb 22)	2.42***	1.87 - 3.13	*0.49*
Feedback spread (Mar 22)	2.53***	1.96 - 3.27	*0.51*
Feedback spread (Apr 22)	2.40***	1.86 - 3.10	*0.48*
Feedback spread (May 22)	1.41***	1.10 - 1.81	*0.19*
Feedback spread (June 22)	1.18	0.92 - 1.51	*0.09*
Feedback spread (July 22)	1.31**	1.03 - 1.69	*0.15*
Feedback spread (Aug 22)	1.18	0.92 - 1.52	*0.09*
Feedback spread (Sept 22)	1.70***	1.33 - 2.19	*0.29*
Feedback spread (Oct 22)	2.80***	2.16 - 3.63	*0.57*
Feedback spread (Nov 22)	2.63***	2.03 - 3.40	*0.53*
Observations	16467		

Note. *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control (May 20)'

Table A6

The evolution of the spread of safety talks for the control department 'CM'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	1.07	0.85 - 1.34	*0.04*
Control (Apr 20)	1.35***	1.08 - 1.69	*0.17*
Control (June 20)	0.82*	0.65 - 1.03	*-0.11*
Control (July 20)	1.01	0.80 - 1.26	*0.00*
Control (Aug 20)	2.16***	1.72 - 2.71	*0.42*
Control (Sept 20)	1.91***	1.53 - 2.40	*0.36*
Control (Oct 20)	1.71***	1.37 - 2.14	*0.30*
Control (Nov 20)	1.16	0.93 - 1.46	*0.08*
Control (Dec 20)	0.83	0.66 - 1.04	*-0.11*
Control (Jan 21)	2.14***	1.71 - 2.69	*0.42*
Control (Feb 21)	3.20***	2.53 - 4.04	*0.64*
Control (Mar 21)	3.68***	2.90 - 4.68	*0.72*
Control (Apr 21)	3.81***	3.00 - 4.84	*0.74*
Feedback spread (May 21)	2.34***	1.86 - 2.95	*0.47*
Feedback spread (June 21)	2.53***	2.01 - 3.18	*0.51*
Feedback spread (July 21)	1.60***	1.28 - 2.01	*0.26*
Feedback spread(Aug 21)	1.63***	1.30 - 2.05	*0.27*
Feedback spread (Sept 21)	1.86***	1.49 - 2.34	*0.34*
Feedback spread (Oct 21)	2.62***	2.08 - 3.30	*0.53*
Feedback spread (Nov 21)	2.82***	2.24 - 3.55	*0.57*
Feedback spread (Dec 21)	1.34**	1.07 - 1.68	*0.16*
Feedback spread (Jan 22)	3.35***	2.65 - 4.24	*0.67*
Feedback spread (Feb 22)	3.27***	2.59 - 4.14	*0.65*
Feedback spread (Mar 22)	5.19***	4.04 - 6.67	*0.91*
Feedback spread (Apr 22)	2.60***	2.07 - 3.28	*0.53*
Feedback spread (May 22)	3.35***	2.65 - 4.24	*0.67*
Feedback spread (June 22)	2.64***	2.10 - 3.33	*0.54*
Feedback spread (July 22)	1.88***	1.50 - 2.35	*0.35*
Feedback spread (Aug 22)	1.91***	1.53 - 2.40	*0.36*
Feedback spread (Sept 22)	2.06***	1.64 - 2.58	*0.40*
Feedback spread (Oct 22)	2.90***	2.30 - 3.66	*0.59*
Feedback spread (Nov 22)	2.53***	2.01 - 3.18	*0.51*
Observations	20328		

Note. *** $p < .01$, ** $p < .05$, * $p < .1$; reference level for interventions 'Control (May 20)'

Table A7

The evolution of the spread of safety talks for the control department 'HM'

VARIABLES	No safety talk		
	Exp (B)	95% C.I.	*d*
Control (Mar 20)	1.35**	1.05 - 1.73	*0.16*
Control (Apr 20)	1.34**	1.04 - 1.71	*0.16*
Control (June 20)	0.86	0.67 - 1.10	*-0.09*
Control (July 20)	0.82	0.63 -1.05	*-0.11*
Control (Aug 20)	0.67***	0.52 - 0.86	*-0.22*
Control (Sept 20)	0.84	0.66 - 1.08	*-0.10*
Control (Oct 20)	1.40***	1.09 - 1.80	*0.19*
Control (Nov 20)	0.96	0.75 - 1.23	*-0.02*
Control (Dec 20)	1.08	0.84 - 1.38	*0.04*
Control (Jan 21)	1.44***	1.12 - 1.84	*0.20*
Control (Feb 21)	2.60***	2.01 - 3.36	*0.53*
Control (Mar 21)	2.85***	2.20 - 3.70	*0.58*
Control (Apr 21)	1.96***	1.52 - 2.52	*0.37*
Feedback spread (May 21)	1.77***	1.38 - 2.280	*0.32*
Feedback spread (June 21)	2.65***	2.04 - 3.42	*0.54*
Feedback spread (July 21)	1.27*	0.99 - 1.63	*0.13*
Feedback spread(Aug 21)	1.17	0.92 - 1.51	*0.09*
Feedback spread (Sept 21)	1.85***	1.44 - 2.38	*0.34*
Feedback spread (Oct 21)	1.98***	1.54 - 2.54	*0.38*
Feedback spread (Nov 21)	1.94***	1.51 - 2.50	*0.37*
Feedback spread (Dec 21)	1.63***	1.27 - 2.10	*0.27*
Feedback spread (Jan 22)	2.29***	1.78 - 2.95	*0.46*
Feedback spread (Feb 22)	1.91***	1.49 - 2.46	*0.36*
Feedback spread (Mar 22)	2.55***	1.97 - 3.30	*0.52*
Feedback spread (Apr 22)	2.50***	1.94 - 3.24	*0.51*
Feedback spread (May 22)	1.93***	1.50 - 2.48	*0.36*
Feedback spread (June 22)	1.69***	1.31 - 2.17	*0.29*
Feedback spread (July 22)	1.30**	1.02 - 1.67	*0.15*
Feedback spread (Aug 22)	1.67***	1.30 - 2.15	*0.28*
Feedback spread (Sept 22)	1.74***	1.36 - 2.24	*0.31*
Feedback spread (Oct 22)	1.72***	1.34 - 2.20	*0.30*
Feedback spread (Nov 22)	1.88***	1.46 - 2.42	*0.35*
Observations	16500		

Note. *** p < .01, ** p < .05, * p < .1; reference level for interventions 'Control (May 20)'

APPENDIX 5A

Figure A1

The Human Factors Analysis and Classification System (HFACS) by Shappell and Wiegmann (2001)

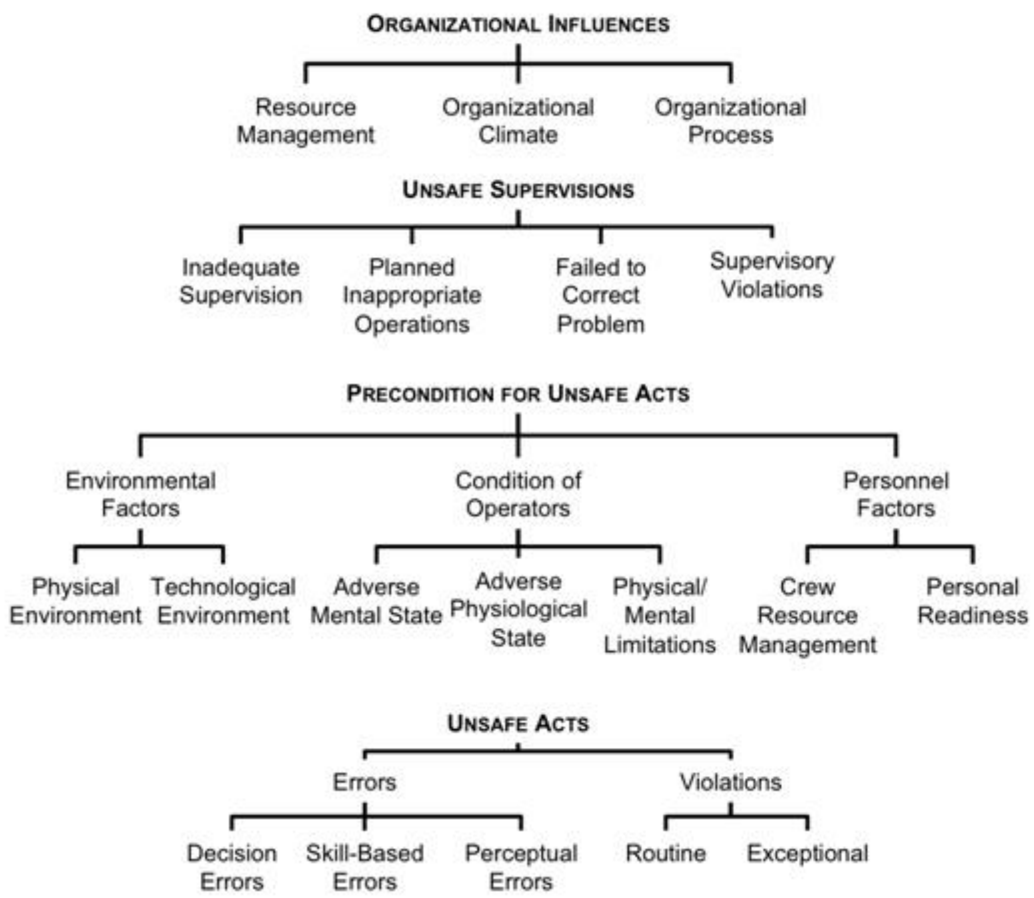


Figure A2

The Swiss Cheese model of Reason (2000), taken from Reason et al. (2001)

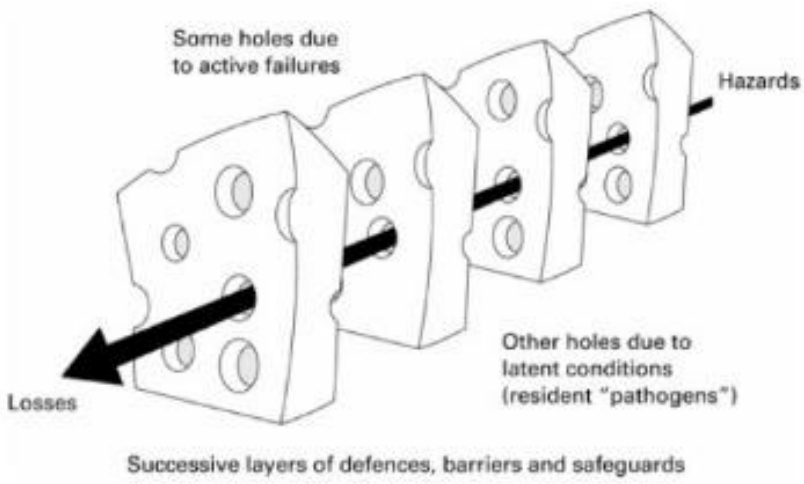
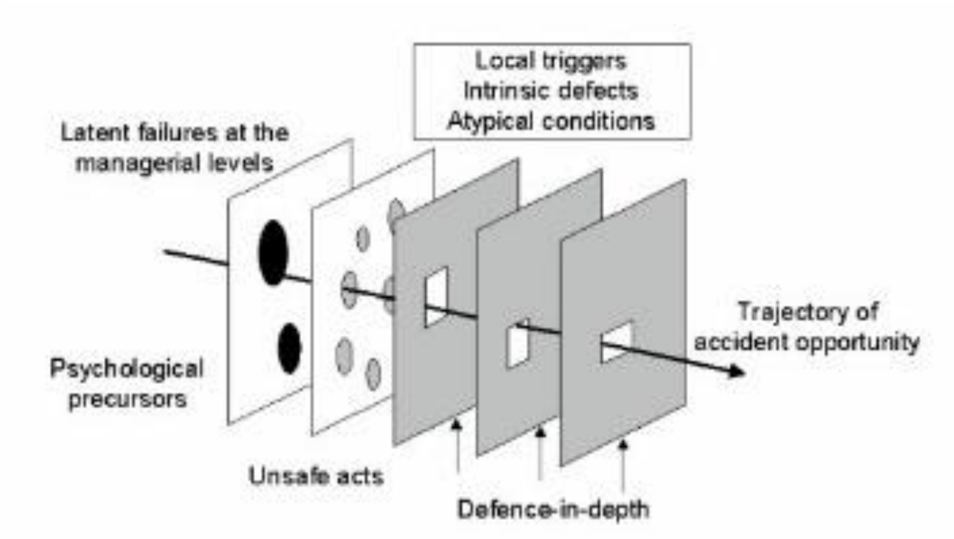


Figure A3

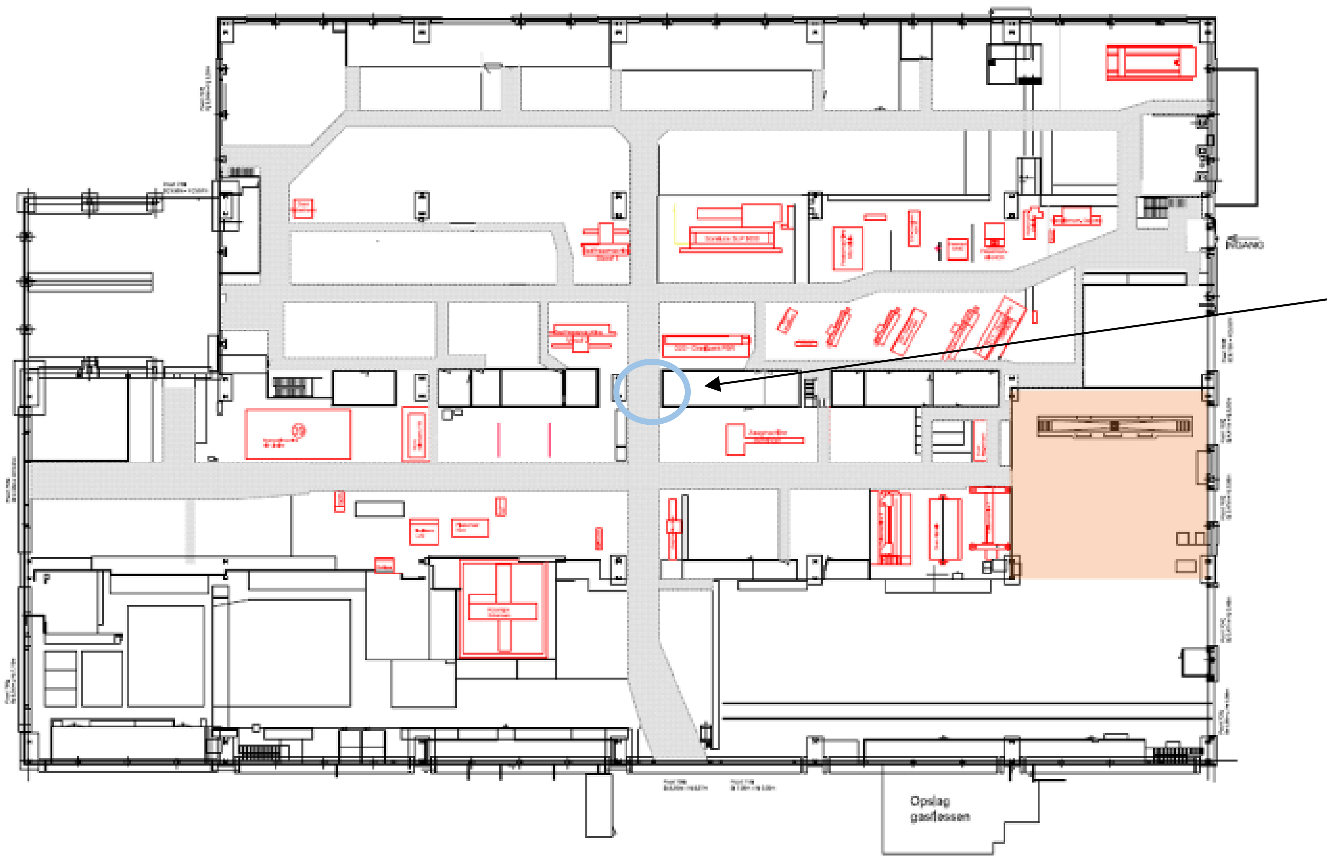
Early stages of the Swiss Cheese model by Reason (1990)



APPENDIX 5B

Figure B1

The floor plan of the central workshop of the General Services (GS) indicating the original placement of the old no-touch tools (arrow) and the workstations (in red)



DATA STORAGE FACT SHEETS

DATA STORAGE FACT SHEET CHAPTER 2

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DATA STORAGE FACT SHEET CHAPTER 3

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  - [ ] file(s) that describe the content of the stored files and how this content should be interpreted. Specify: ...
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