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Creating a workforce of fatigued cynics? A randomized controlled trial of implementing an algorithmic decision-making support tool

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ABSTRACT

In recent decades, public service provision has become increasingly digitalized. However, while digitalization and artificial intelligence holds many promises, there is surprisingly little causal evidence on how it affects the employees who provide such services in the frontline. Based on cognitive and social psychological theories, we argue that IT projects can increase employees' cynicism towards change and change fatigue. In liaison with a Danish unemployment insurance fund, we test our hypotheses in a pre-registered randomized controlled trial that introduced an algorithmic decision-making support tool to underpin the counselling of newly unemployed clients. We do not find evidence that implementation of this tool resulted in negative employee outcomes. However, exploratory analyses indicate that this conclusion may mask smaller or heterogenous effects depending on employees' years of service with the insurance fund. We end the paper by discussing the implications of organizational change in the public sector.

1. Introduction

The advent of digital technologies is widely regarded as having major potentials in improving public service delivery as well as the intra-organizational management of the public sector and digitalization efforts have increasingly contributed to changes in the public sector (Busuioc, 2021). Within this transformation are the algorithmic decision-making tools that use extensive data about citizen characteristics to provide employees in the frontline – the so-called street-level bureaucrats – with statistical predictions about citizen outcomes to ultimately underpin their public service delivery (Zhao & Frank)., 2020). Broadly adopted across various policy areas, these tools are believed to help street-level bureaucrats use their discretion to implement public policies when having insufficient resources to satisfactorily assist citizens, and particularly those facing complex needs, such as poor health, unstable housing, or unemployment (de Boer & Raaphorst, 2021; De Vries, Bekkers, & Tummers, 2016; König & Wenzelburger, 2021; Zhao & Frank)., 2020). Yet, aside from theoretical work regarding the ethical tensions that arise from relying on algorithmic decision-making tools in public service delivery as well as a few case studies, there is astonishingly little empirical research on how such digital changes matter to public service delivery and particularly among the employees who have to implement them in practice (Bernerth, Walker, & Harris, 2011; De Vries et al., 2016). This is surprising as recent research suggests that the adoption of such technologies into public organizations face multiple barriers that ultimately hinder public sector IT projects from delivering on their promises (T. Choi & Chandler, 2020; Maragno, Tangi, Gastaldi, & Benedetti, 2023; Nelson, 2007; Neumann, Guirguis, & Steiner, 2022; Selten & Klievink, 2024). While there is no shortage of aphorisms and textbooks emphasizing the general importance of change management, there is nevertheless a pressing need to understand not only why such digital change processes in the public sector fail to deliver on their promises, but also the implications of project implementation failure for the public organizations themselves as well as their employees.

The implementation of digital technologies in public organizations is indeed far from straightforward. Often initiated from the top down, their success hinge not only on policy design and planning, but also on the degree of pushback, resistance, and other adverse reactions from the local managers and frontline employees who have to implement these policies in practice (Ahmad, Straatmann, Mueller, & Liu, 2021a; T. Choi & Chandler, 2020; Hassan, Zhang, Ahmad, & Liu, 2021; Isett, Glied, Sparer, & Brown, 2013). Change binds a high number of resources and attention that such employees already have too little of to fulfill core job tasks, and this makes it difficult for them to cope with new demanding

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change processes (Fløvik, Knardahl, & Christensen, 2019; Oreg, Vakola, & Armenakis, 2011). Under such strain, employees can potentially face a series of immediate negative consequences, such as increased stress, lower work morale, alienation, and subsequently higher turnover rates (Andrews & Boyne, 2012). But change also might cause contagious or autoregressive failure. The constant pressure of organizational change can affect employees' perception of future reform and modernization (Brown & Cregan, 2008). And this may be especially frustrating if organizational changes are not successfully implemented or lead to clear improvements as the invested resources will then be spent for naught (Bommer, Rich, & Rubin, 2005).

Some of the most focal negative reactions to organizational change are change fatigue and cynicism towards change. Both are core antecedents of organizational malperformance and especially in environments of continual change that require high levels of employee agility (M. Brown, Kulik, Cregan, & Metz, 2017; M. Choi, 2011; Fenton-O'Creevy, 1998; Johnson & O'Leary-Kelly, 2003; Reichers, Wanous, & Austin, 1997; Stanley, Meyer, & Topolnytsky, 2005). However, while existing studies suggest that fatigue and cynicism can accumulate in employees over time (Beaulieu, Seneviratne, & Nowell, 2023; Cox, Gallegos, Pool, Gilley, & Haight, 2022; McMillan & Perron, 2020) and negatively affect both performance and the likelihood of successful change (Andersson & Bateman, 1997; Stanley et al., 2005), surprisingly few empirical studies causally disentangle such organizational change from its effects on employees' attitudes and perceptions (Vito & Sethi, 2020). Understanding whether and how organizational change can be a driver of employee fatigue and cynicism is essential for both researchers and practitioners working with the design and implementation of organizational change processes and change agents' behaviors (Armenakis & Bedeian, 1999, p. 301). This is true not least in the study of the public sector, where we still have scarce knowledge of micro-processes occurring during change (Ahmad et al., 2021a). In order for us to harvest the benefits of new algorithmic decision-making tools to the delivery of public services, we need to understand how they matter as instances of change to work-related attitudes of the employees who use them in practice.

In this paper, we thus aim to address the following research question: "How does an individual change episode relating to algorithm-based tools affect employees' change fatigue and cynicism?" We answer our research question field experimental evidence that enables us to link organizational change to employee change perceptions. Exploiting a (de facto failed) rollout of an algorithm-based decision-support tool to underpin caseworkers counselling of newly unemployed clients across 60 departments of a large Danish unemployment insurance fund, we use a pre-registered randomized controlled trial to assess how employees in departments randomly selected to implement the tool affected their fatigue and cynicism towards organizational change (Reichers et al., 1997). Here, we build a theory of employee change perceptions following change implementation founded in attribution theory, expectancy theory, and conservation of resources theory. We argue that organizational change triggers coping mechanisms that will lead organizational members to attribute blame to other members of their organization. This attribution will interrupt the expectancy link between personal effort and potential future success of projects, eliciting cynicism. Furthermore, the loss of individual resources due to organizational change induces coping, which reduces the willingness to participate in future change, thus increasing change fatigue.

Our results indicate that the effects of a single change episode are limited. Our analysis detects no impact on IT project implementation on either cynicism or change fatigue. Instead, we are able to rule out medium to large negative effects. In an exploratory analysis, we find indications that this conclusion may mask possible smaller effects on cynicism and heterogenous effects on fatigue along employee's years of service, which we argue may relate to temporal and social aspects of fatigue, which is accumulated over longer periods of time and established via socialization processes.

Our study provides three contributions. First, we provide a direct link between classic debates about organizational change, new technologies, and important psychological mechanisms that accompany change projects. While existing studies of change in public sector organizations do consider employee reactions – primary among these employee resistance to change (Kuipers et al., 2014) – the literature lacks the anchoring in psychological mechanisms that our theory provides (see, however, Ahmad et al., 2021a; Hassan et al., 2021; Wright, Christensen, & Isett, 2013).

Second, we provide novel field experimental evidence regarding potentially negative intra-organizational effects of individual IT-driven change processes in public organizations. While there are several observational case and survey studies investigating how employees – and organizations more generally – respond to such developments (Ahmad et al., 2021a; Kuipers et al., 2014; Neumann et al., 2022; Selten & Klievink, 2024), there is little knowledge about causal effects regarding individual episodes of change. Yet obtaining such knowledge is important as observational assessments of the cynicism and fatigue effects of organizational change are vulnerable to endogeneity and reverse causation: Do employees become cynical and fatigued because of change projects, or are projects employed as mechanisms against the downstream effects of employees that are cynical and fatigued? With our experimental setup, we are able to avoid such concerns and provide unique data to the debate about the effects of organizational change on the individual level tested in a real-world setting with high ecological validity.

Third, we provide evidence for the emerging debate about algorithm-based decision-support tools and their effects on street-level bureaucrats. This literature to date is focused on uptake and adoption on the one hand (e.g., Alon-Barkat & Busuioc, 2023; Grimmelikhuijsen, 2023), and on street-level bureaucrats' embedding of decision-support tools in their daily practice on the other (de Boer & Raaphorst, 2021; Rinta-Kahila, Someh, Gillespie, Indulska, & Gregor, 2022). While certainly valuable, these perspectives do not shed light on the unintended consequences of the likely many implementations of decision-support tools that have failed or will fail, due to take-up failure or for other reasons. Our theory and findings provide understanding of the processes that are likely to follow when this happens.

The article is structured as follows: We start out by developing our theory, and corresponding hypotheses, of how project failure may shape employee change cynicism and fatigue. We then present the setting of our study, a Danish unemployment insurance fund servicing mainly blue-collar workers. Subsequently, we present our data, design and approach to estimation. Finally, we provide both an explanatory and exploratory analysis of our data. This is summed up by a discussion of the results, their implications, and the study's limitations.

2. Effects of algorithm-based change in public organizations

Over the past decade, there has been a notable increase in research investigating 'new technologies' related to the advent of so-called artificial intelligence. While the precise definitions of such artificial intelligence are highly debated among scholars (Madan & Ashok, 2023), they examine several types of complex algorithm-based applications employed in various types of public sector organizations (Döring & Hohensinn, 2024). Although definitions of AI have been conceptually contested ever since their first definition in the 1950's, it can described as systems that either act or think humanly and/or rationally (Russell, Norvig, & Davis, 2010, p. 2). The application of AI can, for instance, be based on rules or utilize machine learning (Janssen, Hartog, Matheus, Yi Ding, & Kuk, 2022). Compatible with these broader definitions of

artificial intelligence, this paper uses the concept of algorithmic decision-making referring to "the use of algorithms as an aid or as a substitute to human analysis, to make or inform (and improve the quality of) decisions or actions" (Busuioc, 2021, p. 828).[1]

Within the rapidly expanding literature on AI-related changes in the public sector, we find studies on e.g. factors influencing AI adoption and diffusion (Madan & Ashok, 2023; Selten & Klievink, 2024), risk-assessment tools (Bannister & Connolly, 2020), algorithmic profiling tools (Haug, 2023), chatbots (Androutsopoulou, Karacapilidis, Loukis, & Charalabidis, 2019) (Androutsopoulou et al., 2019), as well as various other forms of decision-making support tools (Zuiderwijk, Chen, & Salem, 2021) that rely on complex statistical models. Madan and Ashok (2023) provide a comprehensive literature review over AI adoption in public administration in which they summarize studies focusing on antecedents and context factors for adoption, implementation strategies, as well as outcomes on various levels.

Interestingly, while Aljuneidi et al. (2023, p. 57) find that "citizens do not generally oppose delegating discretionary power to fully autonomous systems", the situation is likely very different among those involved in public service provision. Indeed, several studies focus on how AI's – be it fully automated systems, humans-in-the-loop and AI as recommender systems – matter to frontline workers' discretion (de Boer & Raaphorst, 2021; Mitrou, Janssen, & Loukis, 2021; Young, Bullock, & Lecy, 2019). Studies for instance find that caseworkers engage in resistance when having to delegate (some of) their discretionary power to AI systems (Haug, 2023, p. 465). Additionally, Sun and Medaglia (2019) empirically demonstrate how different stakeholders (government policy-makers, hospital managers/doctors, and IT firm managers) each have a distinct and opposing perceptions of the challenges of AI adoption. In their empirical study, Strich, F., University of Bayreuth, Germany, Mayer, A.-S., University of Passau, Germany, Fiedler, M., and University of Passau, Germany (2021), find that experienced loan consultants who enjoyed high discretion were negatively affected by the introduction of an AI system and felt their professional role identity threatened. In fact, Anthopoulos, Reddick, Giannakidou, and Mavridis (2016) identifies missing user satisfaction as one of the key reasons to why e-government projects fail (see also T. Choi & Chandler, 2020). This finding is echoed in the literature on information systems (IS), where Nelson (2021, p. 16) suggests that "undermined motivation" is likely to have a more significant impact on productivity and quality of IT projects compared to any other factor. This literature also identifies user cynicism as a great cause of resistance during IT implementation in organizations (Ali, Zhou, Miller, & Ieromonachou, 2016; Selander & Henfridsson, 2012).

Taken together, the existing research has primarily focused on whether and how such tools are used to improve service provision (Androutsopoulou et al., 2019; Chen, Guo, Gao, & Liang, 2021), but does in no way assume that public employees are left unaffected by such changes. Yet, most empirical studies investigating this relationship are based on observational data from case studies or cross-sectional surveys (e.g., Hwang & Choi, 2017). While these provides essential evidence, they fall short of establishing a direct causal link. An exception includes a Swiss randomized field experiment, which showed that the caseworkers, who had access to the statistical profiling tool, "did not change their behavior in any significant way due to having access to the additional information" (Behncke, Frölich, & Lechner, 2009, p. 224) as they either ignored the system or preferred their assessments over that of the tools'. This study, however, did not investigate the impact of using the statistical profiling tool itself. Instead, it focused on comparing the accuracy of predicting unemployment length between caseworkers and the tool (Desiere, Langenbucher, & Struyven, 2019). Another notable exception includes Alon-Barkat and Busuioc (2023) experimental study of automation bias and selective adherence. This study, however, examine the use of algorithms in the public sector in hypothetical scenarios, rather than their effects in a real-world environment. In effect, direct employee-related outcomes are effectively left as a potential 'black box' that deserves further scrutiny (Janssen et al., 2022). How does individual change episodes regarding algorithm-based tools then affect the employees' who implement them in practice?

[1] The algorithmic decision-making tool in this papers' case is 'mixed', in the sense that it entails a human-in-the-loop, that is, the caseworkers maintains their high degree of discretion.

3. A theory of employee consequences of change

Change in the public sector has been examined from a series of different perspectives, from individual change acceptance and resistance to paradigmatic drivers of large-scale, sectoral changes to the public sector as a whole (Kuipers et al., 2014). We anchor our approach in three related theories of organizational behavior: attribution theory (Weiner, 1985), concerned with the causal attributions employees infer from their experiences at work; conservation of resources theory (Hobfoll, 1989), concerned with employees' drives and strategies for obtaining and protecting psychological resources in their work context; and expectancy theory (Vroom, 1964), concerned with the expectations employees have for their environment at work and what happens when these are not met. The gist of our argument is that employees attribute negative experiences with change to their organization and management, view changes as threats to the resources available to them, and that both processes shift expectations to create change cynicism and change fatigue respectively. We cover each mechanism in turn. Fig. 1 provides a sketch of our model.

3.1. Organizational cynicism

Cynicism has been discussed based on a multitude of conceptualizations (Andersson & Bateman, 1997), e.g., as generic distrust of others (Cook & Medley, 1954) or as a basic philosophical outlook which emphasizes that other people are not trustworthy and cannot be depended on (Costa, Zonderman, McCrae, & Williams, 1985). In an organizational context, Dean, Brandes, and Dharwadkar (1998) conceptualize cynicism as an attitudinal construct comprised of beliefs, affects, and behaviors. Here, cynicism combines negatives images of the organization as lacking integrity, honesty, and fairness with negative emotional reactions towards the organization, such as frustration, anger, or distress. Based on these two elements, cynics attune their behavior to have increasingly pessimistic predictions about future developments, explicitly stating their beliefs towards co-workers or other social signals that underline their moral and performative superiority over the organization.

In an organizational change context, cynicism has therefore been defined as "a pessimistic viewpoint about change efforts being successful because those responsible for making change are blamed for being unmotivated, incompetent, or both." (Wanous, Reichers, & Austin, 2000, p. 133). As such, it describes a negative pre-disposition towards future change processes and projects that hamper new change attempts irrespective of their relevance, context, and intent. In this sense, cynicism combines pessimism about the likelihood of future change success with outward blame for failures to other actors that are perceived as either incompetent, malicious, or lazy. Reichers et al. (1997), therefore, argue that cynicism is distinct from skepticism, as "[s]keptics doubt the

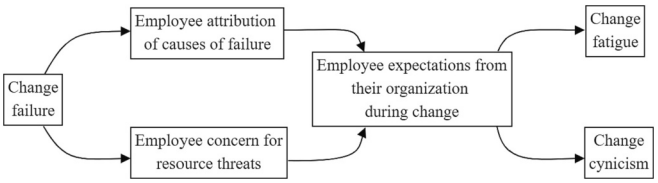

Fig. 1. Theoretical model of individual change failure outcomes.

likelihood of success, but are still reasonably hopeful that positive change will occur." (48). Importantly, Wanous et al. (2000, p. 147) highlights that cynicism should be seen as a learned response than a fixed personality trait. This notion assumes that employees do not deliberately choose to become cynical (Reichers et al., 1997, p. 50) but rather resort to cynicism as a way to make sense of experiences at the workplace.

Accordingly, cynicism can therefore be seen as an individual coping mechanism that makes employees rationalize *why* changes lead to certain outcomes while identifying *who* is responsible for that mechanism. In building our expectations about the relation between organizational change and increasing cynicism, we draw on inspiration from two theoretical angles: attribution theory and expectancy theory.

From attribution theory (Weiner, 1985), cynicism relates to dispositional attribution, that is finding causes for people's behavior in their personal characteristics or abilities (Pettigrew, 1979). In the context of organizational change, outcomes will be attributed to others' performances, inabilities, or motivation (Davis & Gardner, 2004; Wanous et al., 2000). This is done to protect one's self-esteem, especially in the light of future evaluations and tasks (Zuckerman, 1979, p. 266). Attribution styles may thus affect group-level attributions and thereby aspects, such as loyalty and group identification. If self-serving is the main driver for attribution of success and failure, success will be individualized, whereas failure will be socialized, leading to blaming of team members or leaders (Martinko, Harvey, & Dasborough, 2011, p. 145). Thus, experiences of organizational failure may lead to cynicism towards future change in the belief that efforts spent on undergoing change will be futile due to the perceived characteristics or inability of one's colleagues or – even more so – the decision-makers initiating the organizational changes.

With expectancy theory (Vroom, 1964), the mechanism takes a slightly different shape. As a product of three components (expectancy, instrumentality, and valence), people are motivated towards specific behaviors when they believe that their efforts positively affect their performance, and their performance leads to outcomes with favorable rewards. In the context of change cynicism, expectancy is thus of special importance and defined as "a momentary belief on the part of an individual that acting in a particular way will actually be followed by a given outcome" (Behling & Starke, 1973, p. 374). However, experiencing episodes of organizational change failure comes with a risk of breaking this perceived link between effort and performance as the personal resources spent on undergoing organizational change are believed to be only weakly – if at all – related to improved performance, let alone valued rewards.

Combining this perspective with attributional processes described above, this leads to the claim that change failure shifts attribution of success in the work environment away from the individual, which decouples beliefs relating employee actions related to the change from change success. The result is cynicism towards change since employees do not believe themselves able to affect change outcomes. As such, we expect that experiences of organizational change projects will facilitate the occurrence of cynicism towards future change, projected onto the organization as a whole and management in particular (Wanous et al., 2000, p. 135).

H1. *: Experiencing the contested implementation of the risk-assessment tool increases the employee's cynicism towards change.*

This expectation builds on employee beliefs in what they can do to impact changes. The next element of our theory concerns how changes may adversely impact employees.

3.2. Change fatigue

Change fatigue can be conceptualized as the "perception that too much change is taking place" (Bernerth et al., 2011, p. 322). Unlike cynicism, Bernerth et al., 2011, p. 323) argue that neither pessimism and blame attribution are focal elements of change fatigue. Rather, the concept is based on stress and coping literature in which constant organizational change is seen as a source of strain (Fløvik et al., 2019). Following the Conservation of Resources Theory (Hobfoll, 1989), organizational change causes the activation of employees' resources to enact change and adjust to the new circumstances. However, if these change episodes occur too regularly or too frequently, this is likely to trigger resistance to these change processes as the anticipated loss of resources elicits protective reactions in employees (Bernerth et al., 2011). Consistent with this view, as we return to below, resilience and resilience training aimed at building and sustaining employee resources has been recommended as a remedy for change fatigue (e.g., R. Brown & Abuatiq, 2020).

Unlike active change resistance, fatigue is understood as a passive reaction with feelings of ambivalence or powerlessness (McMillan & Perron, 2013). Yet consequences, including for future change efforts, are severe. Change fatigued employees may, for instance, refrain from supporting subsequent changes, lose confidence in organizational leadership, and withdraw from engagement with future changes (de Vries & de Vries, 2023). As such, change fatigue has potential consequences for future change projects as employees will be less likely to willingly accept change and invest their resources to ensure successful changes (Cox et al., 2022; de Vries & de Vries, 2023).

Among the central drivers of change fatigue identified in the literature are rapid and continuous change, intensification of workload, and lack of control (Beaulieu et al., 2023). Change initiatives tend to take time from core tasks and place extra strains on employees' often already thinly stretched resources.[2] Moreover, change induces uncertainty, particularly if employees are tasked with implementing changes for which they do not fully understand the purpose and benefit (de Vries & de Vries, 2023; Van Engen, Steijn, & Tummers, 2019). Finally, as literature on policy alienation proposes (Van Engen et al., 2019; Van Engen, Tummers, Bekkers, & Steijn, 2016), employees are often tasked with implementing policies and policy changes they do not agree with, which could lead to a feeling of powerlessness and perceived lack of control over their work, as well as declines in their willingness to implement policy (May & Winter, 2009; Tummers, Vermeeren, Steijn, & Bekkers, 2012). Consistent with this view, the scant public administration literature on change fatigue – where reforms and changes are often top-down (Kuipers et al., 2014) – argues that changes superimposed on employees in this fashion is a driver of change fatigue (de Vries & de Vries, 2023).

By its nature, failed change may be less likely to result in continuous change or sustained intensification of workload, though failed change might instill a fear that new changes will follow. However, failed change can, as noted above, give employees the sense that they are not in control of what happens to them in their work environment. In addition to decreasing change support among employees (Ahmad, Straatmann, Mueller, & Liu, 2021b), this can have deleterious consequences for employee attitudes and behavior more generally. Employees often react to failed change efforts by turning to defensive tactics such as emphasizing existing organizational routines and rituals and isolation from new input (Goldfinch, 2007, p. 920). This is understandable. If changes, singular or accumulating, are rolled out from the top down, fail, and subsequently rolled back or disappear into the background with little to no impact on daily practice, these changes are likely to become viewed by employees as meaningless, which is a key component of alienation from the policies those changes purport to advance (Tummers, Bekkers, & Steijn, 2009; Van Engen et al., 2016).

[2] The change literature in nursing places a strong emphasis on this due to the fast-paced and emotionally taxing nature of hospital work (Beaulieu et al., 2023). However, as Lipsky (2010), Maynard-Moody and Musheno (2003), and others have noted, many professions working on the front lines of public service delivery faces high demands on their resources due to client demands and other aspects of their work.

Drawing on expectancy theory (Vroom, 1964), the alienation and lack of control employees may experience on the backend of change efforts may alter their expectations from their relationship to their organization. Specifically, employees alienated from change attempts and experiencing a lack of control over what changes they are tasked with implementing become unlikely to reciprocate with enthusiasm. Instead, the tear on employee resources and their resulting defensive stance likely fosters change fatigue, even in the face of changes over which they may have some control or that would be helpful to their daily practice (de Vries & de Vries, 2023). Indeed, due to these factors, Ouedraogo and Ouakouak (2020) argue that change cynicism and change fatigue may be positively related. Based on these considerations, we propose our second hypothesis.

H2. *: Experiencing the contested implementation of the risk-assessment tool increases the employee's change fatigue.*

Several studies have focused on general change fatigue (e.g., de Vries & de Vries, 2023), cynicism (e.g., Audenaert, Van Der Heijden, Rombaut, & Van Thielen, 2021), or both (e.g., Ouedraogo & Ouakouak, 2020). Qualitative studies on said topics include a review of 26 studies of change fatigue in nursing (Beaulieu et al., 2023) and empirical work on change cynicism relating to IT implementation (Selander & Henfridsson, 2012). For public administration, however, there is a substantial lack of evidence on the relationship between individual IT-related change episodes and intra-organizational outcomes. Several studies highlight the cumulative character of both change cynicism and fatigue (Bernerth et al., 2011; Bommer et al., 2005). For example, investigating the Australian Public Service, Wynen, Verhoest, and Kleizen (2019) and Wynen, Boon, and Verlinden (2022) show evidence for detrimental effects of frequent and diverse change episodes on employee outcomes and behavior, such as innovative behavior and turnover intention. Yet, though trajectories of reform may be important for employee attitudes and behaviors (Van Engen et al., 2016), identifying the consequences of adding one more change is of central relevance. Even if change fatigue and cynicism build up across multiple changes, individual changes should have identifiable impacts through the mechanisms we have outlined. It is the identification of such impacts in a field experimental setting we turn to next.

4. Data and methods

4.1. Setting

This study focuses on the Danish unemployment insurance sector. Compared to other countries, the Danish unemployment administration system is traditionally decentralized. Instead of having a single governmental agency providing unemployment benefits, job counselling and educational support are partially tasked to unemployment insurance funds, many of which have traditional bonds to the Danish unions. The funds are legally private organizations that provide official services delegated by the state. Their work is regulated by government, while they enjoy substantial discretion in their organization of operations. Traditionally, funds represent clients from specific work sectors and the fund collaborated with in this study, from here simply “the fund”, focuses on blue-collar workers.

We focus on the implementation of an algorithmic risk assessment tool that was rolled out across 60 departments the fund. The general requirement to implement such a tool was set by the Danish legislator. However, individual funds were free to develop their own tools. While a government developed tool (developed by the government Agency for Labor Market and Recruitment) was widely adapted by other funds, the fund opted to rely on a tool it developed for itself.

The resulting risk assessment tool draws on data about the insured members of the fund (e.g., education, previous employment, age, and geographical information) to develop a statistical model that could predict risks of clients' long-term unemployment during their first meeting in the unemployment insurance fund at the very beginning of their unemployment spell. Here, caseworkers were asked to use a graphical user interface of model output that showed the client's risk of long-term unemployment and as well as the key metrics behind the prediction. The caseworker would then see a traffic-light system, providing simplified information about the client's risk of unemployment. The tool was designed to help underpin caseworkers' job counselling and service provision and help them target resources in a more meaningful way by providing additional support for those at high risk of long-term unemployment, while reducing efforts for ‘easy cases’.

As a specific change episode, it provides us with a highly suitable setting to test our hypotheses. As promising digitalization and new technologies, such as Big Data, machine-learning, or artificial intelligence applications, are at the very doorstep of most private and public organizations, we need a better understanding of the potential challenges to their implementation (Ahn & Chen, 2022). This is particularly relevant to street-level bureaucracy at the frontline of public service provision as they can potentially be perceived as threats to caseworkers' autonomy and thereby affect core elements of the discretionary decision-making (Buffat, 2015; de Boer & Raaphorst, 2021; Selander & Henfridsson, 2012). Moreover, their complex nature will often be perceived as black boxes that could potentially trigger strong emotions and reactions among those using them in practice that potentially differ from the intentions among managers deciding on implementing them into the organization (Busuioc, 2021). Indeed, the preliminary tests during the pilot phase confirmed this expectation as the fund's caseworkers assigned to test the tool had difficulties interpreting the tool's outputs despite the attempt to make predictions transparent by showing feature importance metrics. This is highly relevant as the fund's caseworkers already face the rather difficult task on a daily basis of rightly assessing their clients' potentials, capacities, and motivation for (re) entering jobs. Here, the tool only added complexity and uncertainty to an already saturated decision-making process, which effectively mandated caseworkers to perceive the tool as a resource drain rather than the aid it was intended to be.

4.2. Experimental design

In liaison with the fund's main office, our research team were given the opportunity to support and examine the rollout of the decision support tool in a randomized controlled trial. Based on our input, the fund randomly assigned half of the departments to a treatment group where caseworkers had to use the tool during every first meeting with newly unemployed benefit recipients. In the control group, the caseworkers were not able to use the tool until the investigation period was over. As our research group was given full control the experimental setup including the randomization process, we can test causal claims about the impact of a single change episode on our variables of interest: change cynicism and change fatigue.

The study thereby follows a between-subjects design in which we manipulate one-factor (the introduction of the risk-assessment tool during the first meeting) with two levels. To help ensure that departments were matched on size, we matched departments in pairs based on their number of benefit recipients, and used matched-pair cluster randomization at the level of the fund's departments to randomly assign one department of each pair to the treatment group and the other to the control group. Moreover, to minimize the risk of treatment contagion, we treated two sets of large-city departments with overlapping jurisdictions (three in Odense and two in Copenhagen) as single departments. Study materials, data, code and the pre-registration can be found here: https://osf.io/uk9j2/.

Prior to the rollout, the fund undertook extensive change management efforts for the treated departments. Before their efforts began, we reviewed their change materials and provided input. Change management, of course, is of central importance to change efforts in the public sector (Kuipers et al., 2014), and specifically in the rollout of public

sector IT projects. Materials explaining the operation and purpose of the decision support tool, as well as how it was intended to be embedded in councilors' practice were distributed to treated departments ahead of rollout, with follow-up meetings where department leaders could get clarification, voice objections, and ask practical questions about the tool's implementation. In this sense, the fund followed best practice recommendations for management of planned changes emphasizing purpose, readiness, and inclusion. As we discuss below, this effort may, in fact, have had a positive impact despite the failure of the project's main goals.

4.3. Participants

Our target sample for the survey were all caseworkers employed by the fund during the intervention period. The estimated target population was 282 caseworkers. To base our expectations about effect sizes and statistical power, we rely on the limited empirical evidence about the effects of change occurrences on employees' cynicism towards change or fatigue. One of the few related studies (Andersson & Bateman, 1997) uses vignettes to test the effect of scenarios on respondent's cynicism and found medium effect sizes ($\eta^2 = 0.06$) across different treatments and types of cynicism. Based on that, we assumed that experiencing real-life situations that potentially induce change cynicism are at least as strong in their effect. Thus, calculating the required effect size needed to detect a medium effect size (Cohen's d = 0.5), we aimed for a sample of about 140 to obtain 80% power at a 5% alpha level.

Unfortunately, we were only able to collect a full sample of around 120 responses, which indicates that our minimally detectable effect size is smaller than anticipated. However, we believe that the randomized rollout and high ecological validity of our study nevertheless provides with a fruitful opportunity to test our claims and particularly in light of the very little existing empirical evidence of organizational change on employee cynicism and fatigue. We also follow up our pre-registered analyses below with alternative specifications that are able to extract more power from our sample than our preferred design (see *Estimation* below).

The rollout of the experimental treatment started in February 2022 and ended in November 2022. During the rollout, we collected our data through multiple sources. Administrative data on actual use of the decision support tool are collected by the fund as part of its normal benchmarking procedures. Based on these data, the change effort did not go as intended:

- Participant observation showed that the targeted initial meetings with newly unemployed were packed with procedural requirements about information provision, form distribution, and generic advice. Very rarely was the tool actually considered or a topic on the agenda and had a miniscule effect.
- The take-up rates (on how many newly unemployed clients was the tool applied) in the treatment group surmounted to only 12%. This is far below the expectations by the agency's headquarters.
- Interviews with several caseworkers showed that acceptance and perceived usefulness of the new tool was very low and particularly among caseworkers with longer tenure.

Since these issues were not products of tool design, timeliness, nor budget, but with end users' reluctance to use it, we can – with terminology borrowed from the study of information system implementation – label the process a clear instance of “user failure” (Goldfinch, 2007). Since failure and success of change efforts are rarely evaluated in the literature on public sector change management, in part due to the difficulty of determining whether initiatives fail or succeed and on what criteria (Kuipers et al., 2014), this unfortunate outcome does provide us with a rare opportunity to study employee impacts during change failure. Responding to this opportunity, we surveyed the caseworkers between late September and mid-October 2022 to learn about their experience of being exposed to the tool. Thus, our data collection period is approximately six months into the implementation period, we argue that this effectively provides us with solid test of our hypotheses as the period of initial uncertainty about the tool will likely have subsided. Concurrently, however, the delay does make us able to distinguish stable change cynicism and fatigue from any results of initial confusion that change management practices could still clear up in the project's early stages.

4.4. Measures

For our main results, we measured change cynicism and change fatigue in the survey. All survey items can be found in the appendix.

4.4.1. Change cynicism

Change cynicism consists of four items that have been adapted from Stanley et al. (2005). The items cover the emotional distance to the change-specific tool, skepticism towards the management's goals, and a pessimistic pre-disposition towards the likelihood of success of such digital instruments. The final scale was measured on a 5-point Likert scale and shows a good measurement reliability with McDonald's omega of 0.84.

4.4.2. Change fatigue

Change fatigue consists of a three-item instrument adapted from Bernerth et al. (2011). It covers the more general perception of depletion and exhaustion due to change processes in the past. Again, the McDonald's omega is 0.90 which is considered as a good measurement reliability.

We ran confirmatory factor analysis for both measurement models and found very high factor loadings and model properties: $\chi 2(df\ 13) = 18.195$; CFI = 0.987; TLI = 0.980; RMSEA = 0.060 (90% CI, 0.000–0.120); SRMR = 0.037). We identified latent variables using effects code, utilizing constraints on factor loading and item intercepts to ensure that the latent variables are on the same scale as their indicators. From this model, we extracted factor scores and used these as dependent variables in the subsequent data analysis.

4.5. Estimation

We employ ordinary least squares regression in all our models. To account for the match-pair randomization procedure, we employ fixed effects for pairs in all models. Since our design employs cluster randomization at the department level, we cluster standard errors in our models on department.[3]

Provided our lower-than-anticipated number of collected observations from an already limited target population, we follow up our main analysis with a more well-powered, exploratory assessment of our hypotheses. Specifically, we re-estimate our models in a repeated measures framework, utilizing the response for each individual item for change cynicism and fatigue as a within-respondent observation. We run these models with fixed effects for pairs as well as for items, and cluster standard errors by departments and individuals. Effectively, this approach trades increased power for increased measurement error,

[3] This approach can be comparatively inefficient since it compares only within pairs rather than utilizing partial pooling as a (random effects) multilevel model would. However, given our match-pair randomization, we consider the fixed effects approach appropriate. A multilevel specification provides qualitatively similar results to our preferred estimation procedure.

which the latent variable framework is designed to eliminate. Provided our smaller-than-expected sample size, however, we opt to provide this follow-up analysis on the view that it reduces the risk of Type-II errors.[4]

5. Results

The results of our pre-registered analysis are presented in Table 1. For cynicism towards change, the data indicate that being part of the treatment group (participating at a rollout of an IT tool) leads to higher levels of cynicism (see also Fig. 2). However, the *p*-value is above our pre-registered accepted level of 5% and thus not significant. The general trend in the data might point to the aforementioned power issue due to our sample size. The size of the estimated effect is small and precisely estimated ($d = 0.258, 95\%CI = [-0.153, 0.670]$). This means that we can rule out at conventional confidence levels unexpected negative treatment effects of any substantial size as well as very large effects in the expected size. However, our analysis cannot conclude that only small effects obtain due to inefficient estimates. Only 38% of the sampling distribution is within a 0.2 standard deviation region of practical equivalence (ROPE). 87% is within a 0.5 standard deviation ROPE. For change fatigue, the results are less indicative of direction but more indicative of effect sizes we can rule out. The estimate is not significant at conventional levels, and the coefficient even points in the opposite direction than our pre-registered hypothesis H2 indicates. On the other hand, the estimate is more precise, permitting us to rule out with some confidence both large, and counterintuitive, negative effects and anything but relatively small positive effects ($d = -0.136, 95\%CI = [-0.523, 0.252]$). 59% of the sampling distribution is within a 0.2 standard deviation ROPE, whereas a full 96% is within a 0.5 standard deviation ROPE. Fig. 3 shows the unstandardized average treatment effect for both cynicism and fatigue.

While the insignificant results in model 1 may be attributable to a lack of statistical power and imprecise estimation, our null finding in model 2 comes as a bigger surprise. One plausible explanation could be that change fatigue is not easily attributable to a single change event, but rather a process nourished among caseworkers with a history of previous change (Beaulieu et al., 2023; Ouedraogo & Ouakouak, 2020; Van Engen et al., 2016). An extension of this line of reasoning is that effects on fatigue masks unanticipated heterogenous treatment effects since some caseworkers will have experienced more change than others. To further examine these plausible explanations for our findings – lack of statistical power and effect heterogeneity –, we deviate from our original pre-registration to conduct additional post-hoc analyses. The following analysis should thus be considered as purely exploratory, providing additional impetus for future replications and studies. The statistical conclusion of our main analysis, however, is that the analysis cannot detect the expected effects but that this could be due to a lack of power or, possibly, heterogeneity in effects leading to imprecise effect estimates. The clearest signal in our data is that we can rule out medium or larger effects of support tool implementation on change fatigue in the expected direction.

Table 1
Linear fixed-effects models with fixed effects for matched pairs and clustered at department level.

	(1) Cynicism (H1)		(2) Fatigue (H2)	
	Estimate (unstandardized)	p-value	Estimate (unstandardized)	p-value
Treatment (Support Tool)	0.200 (0.136)	0.147	−0.121 (0.148)	0.419
Observations	122		119	
Pairs	30		30	
Adj. R2	0.019		−0.043	

Note: $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$ (two-sided tests); results are clustered at the department level
and use fixed effects for the matched pairs; standard errors in parentheses.

5.1. Post-hoc analysis

Our post-hoc analysis aims to handle two issues: 1) address the limited statistical power of our data, and 2) investigate potential heterogenous treatment effects along experience with change.The aim is to parse through possible reasons for the null findings we reported above, attempting to provide guidance for future research.

To gain leverage on these questions, we changed the operationalization of our dependent variables to provide us with a more powerful design that enables additional tests of our hypotheses and potential interaction effects, again, with the purpose of attempting to disentangle lack of power, heterogeneity, and null effects as sources of our null findings.

In order to strengthen our statistical power, we therefore turn our factors into a repeated measurement framework. Instead of combining the individual items into a single measure, we use the single items as individual measures, leaving us multiple observations for each outcome variable for each caseworker. We add fixed effects for items to the model to soak up differences between items across individuals, and cluster standard errors by respondent as well as by department. While this approach boosts our number of observations, it comes with the clear caveat of inflating potential measurement errors. To be clear, our primary measurement model is preferable to this as it makes less stringent assumptions in its measurement model. Yet, the repeated measures framework serves the forward-leaning purpose of the post-hoc analysis better.

Based on the repeated measures approach, we reassessed the average treatment effects of our treatment on both our dependent variables. As the results of Table 2 show, this model detects an effect on cynicism towards change in the expected direction (Est = 0.263, $p = 0.038$). The detected effect is relatively small ($d = 0.274, 95\%CI = [0.024, 0.523]$). 28% of the sampling distribution is within a 0.2 standard deviation ROPE, wheras 96% is within a 0.5 standard deviation ROPE, indicating that the model is inconsistent with even medium size effects of the treatment. The results for change fatigue are qualitatively consistent with our primary estimate (Est = −0.019, $p = 0.897$), tending to support that the implementation of the assessment tool does not impact change fatigue even in a more well-powered setup. The estimated effect size is near zero and its precision sufficient to rule out medium size effects ($d = -0.026, 95\%CI = [-0.311, 0.260]$). Around 82% of the sampling distribution for the estimate lies within a 0.2 standard deviation ROPE. >99% is within a 0.5 standard devation ROPE, indicating that any effects that we may obtain are likely to be of small practical importance.

The finding for fatigue could, however, be due to buildup of changes over time being of more relevance than our initial theorizing anticipated. Change fatigue could increase as a result of the introduction of the assessment tool, but only for caseworkers having experienced many prior changes over their time working for the fund (Ouedraogo & Ouakouak, 2020; Stensaker & Meyer, 2011). To investigate this, we interacted our treatment with the employees' tenure in the fund. We show the resulting model for both cynicism and change fatigue for the sake of completeness, but the expectation that effects will be moderated are by far the strongest for fatigue. Results of the moderation analyses are given in Table 3. We add controls to the models account for potential

[4] A reduction in Type-II errors is not a necessary consequence of the repeated-measures approach since increased measurement error could result in failing to reject true alternative hypotheses. However, with a three to four-fold increase in the number of observations, we view it as unlikely that this effect overpowers the benefits of increased power in this respect.

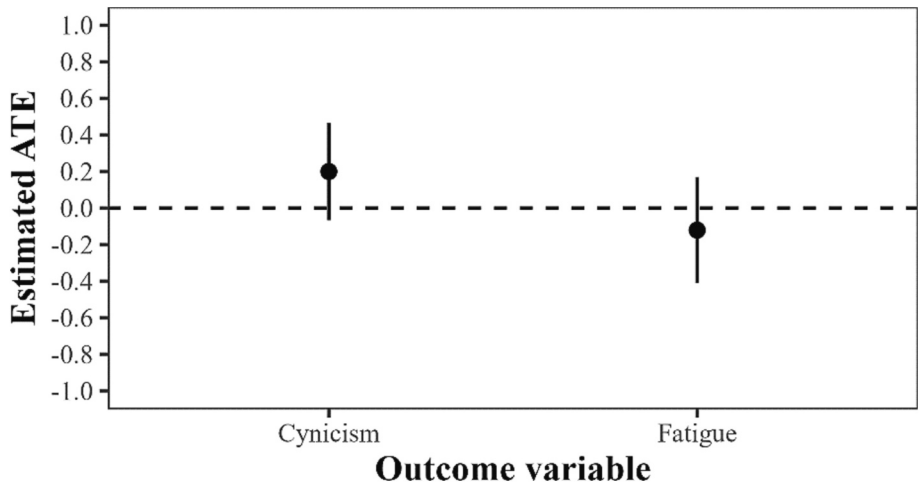

Fig. 2. Estimated average treatment effect.

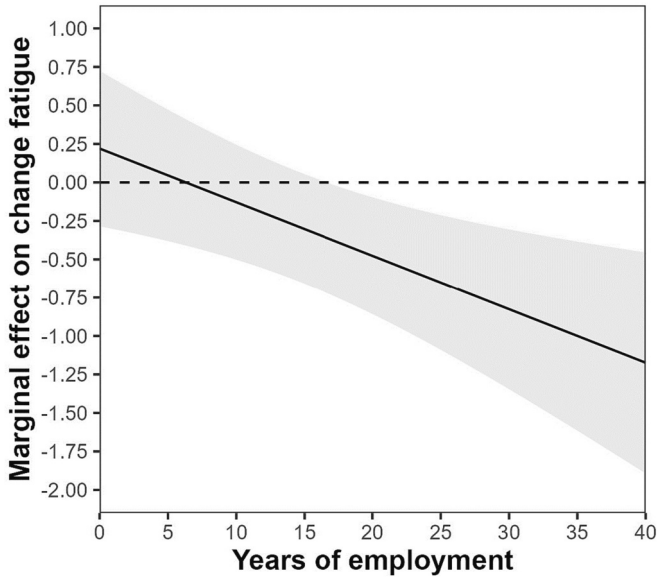

Fig. 3. Post-hoc Interaction Effect of Tenure and Treatment on Change Fatigue.

Table 2
Post-hoc fixed effects models for average treatment effects using repeated measures.

	(1) Cynicism (H1)		(2) Fatigue (H2)	
	β	p-value	β	p-value
Treatment (Support Tool)	0.263* (0.124)	0.038	−0.019 (0.146)	0.897
Adj. R^2	0.128		0.103	
n	488		359	

Note: $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$; results are clustered at the department level and use fixed effects for the matched pairs; standard errors in parentheses.

endogeneity of our moderator variable (since we did not induce change in caseworker tenure). The included control variables are Age (in years), Gender, Education (measured in categories distinguishing primary/secondary education from professional education, tertiary education, and other education), and position (department leader vs. councilor).

For cynicism towards change, we find no relevant interaction effects,

Table 3
Post-hoc Fixed Effects Models for with Interaction Terms.

	(1) Cynicism		(2) Fatigue	
	β	p-value	β	p-value
Treatment	0.415 (0.257)	0.113	0.220 (0.257)	0.397
Tenure	−0.0014 (0.0119)	0.905	0.035* (0.011)	0.003
Treatment*Tenure	−0.013 (0.014)	0.364	−0.035** (0.013)	0.008
Controls	Yes		Yes	
R^2	0.223		0.336	
n	408		299	

Note: $p < 0.001 = ***$; $p < 0.01 = **$; $p < 0.05 = *$; results are clustered at the department and individual level; matched controlled for matched pairs; standard errors in parentheses. A table including estimates for control variables is included in the Appendix.

which as noted is not surprising, but still does help bolster the conclusion that our primary null finding for cynicism is at least not due to heterogeneity based on years serving the fund. For change fatigue, we find that tenure has a positive relationship with change fatigue. The longer employees are a member of an organization, the more change fatigue builds up over the course of their career. This finding echoes previous findings in the existing literature, suggesting that as more tenured members of an organization accumulate experiences of multiple change episodes, they develop a change fatigue over time (Assadi & Lundin, 2018; Babalola, Stouten, & Euwema, 2016; Ouedraogo & Ouakouak, 2020; Stensaker & Meyer, 2011).

What is remarkable in our data, however, is the direction of our interaction term. One would expect that experiencing this additional episode of change in our experimental setting will further increase the change fatigue. However, our exploratory model indicates the opposite: Being a participant in the treatment group stalls further change fatigue explaining the inconclusive main effects of the treatment on fatigue. In the control group, as Table 3 indicates, we observe the expected positive association between tenure and fatigue. In the treatment group, this association all but disappears. As a result, the marginal effects of our treatment – rather than increasing with tenure – decreases with years of employment with the fund such that there is no detectable effect for caseworkers with fewer years of experience, whereas caseworkers with 16 or more years of experience experience less change fatigue when allocated to the treatment group.

Of course, while this result is surprising, it is an outcome of our exploratory analyses and thus needs to be interpreted with some

caution. As noted, the main conclusion of interest here is whether years of employment can be feasibly included as a plausible moderator in future confirmatory studies. We hesitate to make substantive conclusions about this based on our analysis. Yet, given the surprising direction of the moderation we detect, we end our discussion of results with some reflections on whether future studies ought to expect the same. We argue, essentially, that the answer depends on context. Specifically, we see two feasible interpretations, respectively related to change management and project failure.

On the change management side, we could interpret the result as indications that the fund's change management activities accompanying the implementation process were successful. Change management efforts in the treatment group ameliorated the build-up of change fatigue among longer-serving caseworkers. This could lead to the observed negative effect if efforts reduced change fatigue beyond what longer-serving members of the control group had built up from prior changes. As such, change management might have a preventive effect on the negative consequences of constant change in organizations (Beaulieu et al., 2023). Especially considering the context of our study, this project was one among the first in which change management has been explicitly used to facilitate the project rollout within the fund.

This finding would call to our attention that studies on change processes should anticipate and incorporate a potential 'change legacy' that might affect expectations and prior attitudes of new change episodes, but also to the role change management can play in reducing the build-up of resource strains from such a legacy. Our treatment, from this perspective, is a compound treatment of the change itself, and change management efforts that may have helped explain to longer serving caseworkers the purposes, intentions, content, and impact of the change. Future studies collaborating with organizations on IT-related change effects on change fatigue may do well to take this into account. Not only may change management be helpful for mitigating negative consequences of such changes, but its impact could be heterogenous along employee's prior experience. Average treatment effect estimates mask this heterogeneity, but it can be of great practical interest.

This leads to an alternative interpretation of the moderation effect our exploratory models identify. The change we studied failed to gather impact on the daily practices of many caseworkers, despite being announced and sought implemented with some fanfare during the rollout phase. This may have shown caseworkers that resistance is not futile, and that the build-up of change initiatives – or more specifically the impact of this build-up on their daily routines – is partly within their control. In fact, it may have proven these caseworkers that they actually possess the real power to implement this (and future) IT-systems, reassuring them in their worth for the organization rather than – for instance – posing a threat to their profession. Tenured caseworkers in the treatment group may thus have concluded that they were indeed able to resist, forestall, or dilute coming changes. Because caseworkers in the control group did not have this experience, their hopes for future resistance do not alter this way, leading to the moderation effect we observe. This interpretation, in a sense, is good news for organizations operating in public environments where resistance is common, and change is difficult. Though the project did not serve its intended purpose, the addition of it to the 'change legacy' of the organization does not seem to add change fatigue downstream. The bad news, of course, is that this conclusion does not seem to hold for cynicism in our data, and – owing to the exploratory nature of the analysis detecting it – awaits confirmatory examination before we would recommend practitioners lean on it too heavily. Such future studies, in light of this interpretation, may benefit from considering the autonomy and capacity of particularly experienced employees to steer clear of deep implementation and, through this, avoid fatigue build-up.

We are not able with our data and design to tease these interpretations apart. However, our findings in the exploratory moderation analyses do emphasize the need for research on public sector change to better understand the implications of project failure, rather than just their causes. This is especially relevant for politically coerced projects, such as the profiling tool in our case, since public organizations are generally more likely to experience coercive isomorphism and external pressure causing organizational change (Frumkin & Galaskiewicz, 2004).

Furthermore, it is notable that the ICT system in this specific case is a profiling algorithm that predicts members' risk of long-term unemployment rather than, say, a new journal or database system, which is more widespread in public bureaucracies (Busch & Henriksen, 2018, p. 17). This ICT system mimics the high discretion task of the front-line caseworker concerning the assessment of the unemployed chances to (re-)enter the labour market (Young et al., 2019). The caseworkers in the treatment group had daily discussion of and around the tool in the tested period – also with decision-makers higher up in the organization. These caseworker-caseworker and caseworker-organizational decision-makers discussions supported their work-practices following the introduction of the tool. The treatment group caseworkers could thus assess the reliability and usefulness of the algorithm's outputs in comparison to their own judgment. For instance, they could compare the significance of parameters in the algorithm such as region, type of industry and gender to their own past experiences and knowledge of the local labor market. Additionally, they could compare different cases of members' prediction of long-term unemployment with each other, further stimulating a key part of their work practice, namely servicing the member. In this change management process, the caseworkers' discussion of and around the tool actually/critically enabled their very discretion (Buffat, 2015), although they, remarkably, in practice neglected using the tool.

6. Conclusion and limitations

Our study investigated the negative effects of change processes, specifically a public sector IT project that makes use of algorithmic decision-making support tools. Based on conservation of resources theory, expectancy theory, and attribution theory, we expected to find detrimental effects to employees' cynicism towards change and change fatigue in the light of an (ultimately failed) IT project. However, our data does not support our pre-registered hypotheses. Instead, they enable us to conclude only that expected effects were at least not large – for cynicism – and medium or large – for change fatigue. For practitioners, this may be good news, in the sense that our data do not support a fear that IT projects of the type we consider result in large-scale negative employee outcomes.

Our post-hoc analyses, however, indicate that managers should not be overly optimistic. In these analyses we do find indications for a small effect on cynicism. Though not confirmatory in nature, this conclusion provides an angle for future research on organizational change and IT implementation in the public sector: larger-scale studies than ours may be able to detect effects. Whether these are of interest to managers is a different question. Our exploratory analyses an even more complex picture of the effect on change fatigue. Specifically – while they indicate no substantive average effect of IT project implementation – this may mask differences that are legacy dependent. Theoretically, change fatigue has a stronger temporal element to it that accumulates up over time. In our data, however, this accumulation does not appear to operate in straightforward ways when projects are rolled out with the use of change management tools and/or when they fail to impact employees' daily practices. Accumulation has also been discussed in relation to attribution theory. Harvey et al. (2014, p. 139f) call for research that investigates the temporal aspects of failure attribution over longer periods of time. Longitudinal designs that track successful and unsuccessful projects within organizations over time could shed light into these dynamics and may help further understanding on our primary conclusion that we detect no substantial effect on change fatigue on average.

Naturally, our study comes with limitations and caveats. First and foremost, the effect size of cynicism and change fatigue were smaller

than anticipated and our design was not powered to detect small effects. This might indicate that individual change episodes are less relevant than we expected them to be – at the very least, they do not result in large effects on employee cynicism. This has consequences for the purposeful study of detrimental effects of organizational change. If individual episodes do not provide sufficient evidence, more comprehensive methods of investigation are needed. Case studies that incorporate qualitative approaches, such as ethnographic methods, would be well-suited to accompany organizations over long periods of time and gain rich information (Ospina, Esteve, & Lee, 2018) about long-term developments of cynicism towards change as well as change fatigue.

Second, we studied the causal impact of a change and did not manipulate or control the process of how this change was implemented or whether implementation impacted daily practice. As part of our efforts to assist with change management, we did seek to help the Fund successfully implement the change, but we did not experimentally control either process or outcome. As a result, the relationship between change failure, change cynicism, and change fatigue is not discernable in our data. We did not set out to study this relationship, but it is relevant. Our design permits identification only of whether implementation *tout court* contributed to cynicism; not of whether cynicism contributed to implementation failure, or whether implementation failure contributed to cynicism. Either is possible. For this reason, we urge future research to dive into examining employee impacts of project failure, including cynicism.

Third, the risk of spillover effects is inherent to most field experimental designs. In our case, it is not impossible that cross-departmental communication might have affected employees' perception of the tool. Generally, the fund's departments are structurally autonomous, self-governing, and geographically distributed across the whole country which makes spillover effects less likely. However, we cannot rule out cross-departmental communication between local managers at management group meetings which might have seeped into their respective departments. While this would not affect the treatment allocation itself as the tool was only available for counsellors in the treatment departments, we cannot rule out that perceptions of the tool – both negative and positive – could travel across departments. But it is difficult to say whether such processes shape our results, and moreover whether said effect increase and decrease the effect size.

Fourth, the professional background of our investigated organizations might provide a specific case for the effects of algorithmic decision-making support tools. As Bullock (2019) highlights, professions might react to algorithmic or AI-based tools depending on how they affect their professional discretion and work. In organizations, where professions are less relevant, the effects of single change episodes or long-term change might differ accordingly. Similarly, the employment policy context – where employees already face a number of regulatory demands on their practice and are somewhat limited in their discretion – and the Danish national context – where trust is relatively high, and users are professionally tied to the employment services they receive (and which they pay for through contributions to the fund) – can impact the effects of changes on employees. Comparative studies could, thus, inform us about such organizational and contextual factors (Buffat, 2015). Finally, generalizations of our findings to implementation of IT projects should be done with care if implemented systems differ substantially, e.g., systems that automate decisions, since system characteristics may influence system impacts on employees' daily practice.

Fifth, one might argue that the caseworkers' fatigue and cynicism levels may in part be reverberations from the COVID-19 pandemic. While the pandemic and the subsequent lockdown of the unemployment services clearly mattered to how unemployment services were delivered, the impact on the psychological strain of public employees – as well as their citizens – were not exclusively negative due to temporary policy changes (Bækgaard, Mikkelsen, Madsen, & Christensen, 2021; Kommunernes Landsforening (KL), 2020). But most importantly, the pandemic's impacts on psychological outcomes should not affect results due to our experimental setup; though we cannot rule out that the pandemic provides additional context to our estimates that may limit their generalizability (Döring & Hohensinn, 2024).

Lastly, replications will be needed to solidify our claims, especially those from our exploratory post-hoc analysis. As algorithmic decision-making support tools are becoming more and more prevalent, the importance of investigating the implementation of such tools, as well as the failed implementations, will be an important topic to the research field. Our analyses indicate that future analyses will need to balance a more well-powered design than ours against effect sizes that managers and other practitioners care about. We rule out large effects, but in some contexts, practitioners may be concerned also with smaller negative effects on employee outcomes. Additionally, our exploratory analyses indicate that employee and organizational change histories may need to be considered when designing future studies in this space.

Thus, we hope that our investigation provides a new angle to the study of IT projects and change processes by highlighting the potential temporal and social dynamics underlying the perception of change in organizations. The current wave of new IT-based tools, especially in government organizations, puts a severe strain of its members which is why change needs not only to be management, but also planned strategically.

CRediT author statement

Döring: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization.

Mikkelsen: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Investigation, Resources, Project administration, Visualization.

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CRediT authorship contribution statement

Matthias Döring: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Kim Sass Mikkelsen:** Conceptualization, Formal analysis, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. **Jonas Krogh Madsen:** Conceptualization, Investigation, Methodology, Project administration, Resources, Writing – original draft, Writing – review & editing. **Kristian Bloch Haug:** Writing – original draft, Writing – review & editing.

Declaration of competing interest

None.

Appendix A

Measurement of variables

Cynicism*:*

Following, we would like to hear your thoughts about XXX (anonymized) statistical profiling tool, that shall help assessing unemployed's risk of

long-term unemployment.

How much do you agree with the following statements? (1 – strongly disagree to 5 – strongly agree)

- The statistical profiling tool is part of a trend that will vanish as quickly as it emerged.
- I am skeptical of the motives behind the introduction of the statistical profiling tool.
- I experience that there is a 'hidden agenda' behind the introduction of the statistical profiling tool in counselling.
- I am skeptical whether the statistical profiling tool actually works.

Change fatigue*:*

Following, we would like to hear your thoughts about the changes that you experience as an employee at XX (anonymized).

How much do you agree with the following statements? (1 – strongly disagree to 5 – strongly agree)

- We are in need of a period of stability at XXX before we introduce more change.
- I am tired of all the change that is happening at XXX.
- Way too many changes are introduced at XXX.

Tenure: How many years have you been employed at XXX (anonymized).

Education: What is your highest degree?

- Primary education (9 years)
- Secondary education (10 years)
- Higher secondary education (12 years)
- Occupational degree (trades and crafts)
- Short further education (e.g., information technologists, dentist)
- Medium further education (e.g., pedagogue, engineer)
- Long further education (e.g., lawyer, pharmacist)
- Other

Age: How old are you?

Female: What is your gender? (Male / Female).

Leader: [those respondents that have additional management obligations].

Appendix B

Table 4

Post-hoc Analysis Fixed Effects Models for with Interaction Terms and Controls using Repeated Measures.

	(1) Cynicism		(2) Fatigue	
	β	*p*-value	β	p-value
Treatment (Support Tool)	0.415 (0.257)	0.113	0.220 (0.257)	0.397
Tenure	−0.0014 (0.0119)	0.905	**0.035* (0.011)**	**0.003**
Treatment*Tenure	−0.013 (0.014)	0.364	**−0.035** (0.013)**	**0.008**
Controls				
Age	−0.004 (0.010)	0.673	0.008 (0.012)	0.489
Female	−0.144 (0.191)	0.456	**0.426 (0.207)**	**0.050**
Education: Primary	(Baseline)		(Baseline)	
Education: Professional	**0.451 (0.255)**	**0.083**	−0.013 (0.322)	0.968
Education: Tertiary	0.201 (0.245)	0.416	−0.373 (0.286)	0.198
Education: Other	−0.497 (0.358)	0.170	−0.772 (0.573)	0.184
Team leader	−0.551 (0.346)	0.117	−0.903 (0.560)	0.113
Multiple Measure: Cyn or Fatigue 1	(Baseline)		(Baseline)	
Multiple Measure: Cyn or Fatigue 2	**0.441 (0.093)**	**<0.001**	**−0.570 (0.083)**	**<0.001**
Multiple Measure: Cyn or Fatigue 3	−0.059 (0.109)	0.590	**−0.590 (0.085)**	**<0.001**
Multiple Measure: Cynicism 4	0.137 (0.014)	0.364		
Controls	Yes		Yes	
R^2	0.223		0.336	
n	408		299	

Note: p < 0.001 = ***; p < 0.01 = **; p < 0.05 = *; results are clustered at the department and individual level; matched controlled for matched pairs; standard errors in parentheses.

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