How does Algorithmic Decision-Making Support Affect Street-Level Bureaucrats Service Provision?

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Disclaimer: This is an extended project description as data collection has been postponed due to the recent pandemic. However, we provide anecdotal evidence from observations and interviews collected during the test-phase of the project rollout. Any suggestions on theory, design, or measurement are highly welcomed.

Algorithm-based decision-making has gained increasing attention in the public administration literature over the past years (Androutsopoulou et al., 2019; Aoki, 2020; Busuioc, 2020; de Boer & Raaphorst, 2021; Kolkman, 2020; Larsson, 2021; Meijer et al., 2021; Young et al., 2019). The advent of AI-induced technologies, big data, and other related techniques provide organizations with tools that promise substantial benefits regarding efficiency, processing capacity, but also new approaches to increase the effectiveness of public services (Young et al., 2019). Based on early studies that discussed challenges with digitalization efforts of the past decades (Buffat, 2015; Busch & Henriksen, 2018), researchers have examined how employees, such as street-level bureaucrats, perceive and react to these new tools (Assadi & Lundin, 2018; Gillingham & Humphreys, 2010). Seminal work has investigated how contextual factors shape the implementation of AI-induced technology (Meijer et al., 2021), but also how employees' behaviors and routines may be challenged by it (de Boer & Raaphorst, 2021; Ranerup & Henriksen, 2020). Simultaneously, studies addressed how citizen think about these new tools. Various studies indicate general reluctance towards automated or semi-automated processes and artificial intelligence (Aoki, 2020; Caswell et al., 2010; Eubanks, 2019; Zejnilović et al., 2020). While algorithms are often criticized for reinforcing discriminatory patterns underlying the data they are built on (Andrews, 2019; Busuioc, 2020), there is also evidence that minority groups may also view them as a potential remedy for existing discrimination as human biases may be avoided (Miller & Keiser, 2021). Nevertheless, we know very little about whether these tools can actually improve organizational output and effectiveness. Hence, our study addresses this research gap. By conducting a field experiment in a large Danish unemployment agency, we assess whether the introduction of an algorithmic risk-assessment tool to assess potential long-term unemployment improves the quality of consultation services and helps to bring more people back to work.

Therefore, our study offers three contributions. First, we provide unique evidence for the effectiveness of algorithmic decision-making support tools. Second, we investigate how this effectiveness depends on the personalization of consulting efforts. Third, we examine boundary conditions that affect whether recommendations provided by the tool are translated to action. Specifically, we examine the role clients' self-efficacy as well as the perceived informational and procedural justice regarding the consultation.

Theory

Street-level bureaucracy is typically characterized by professionals implementing public policies using their discretion to translate broader legal frameworks to the complexity of reality (Baviskar & Winter, 2016; Brodkin, 2015; Lipsky, 2010; Maynard-Moody & Musheno, 2003; Tummers et al., 2012). For that purpose, they often build on their specialized education, norms, and values (Brodkin, 2011). However, as Lipsky (2010) points out, street-level bureaucrats, such as caseworkers, suffer from a systematic struggle for resources, as there is a sheer unlimited demand for their services. At an individual level, caseworkers will make use of various coping strategies to solve this struggle. At the organizational level, digitalization and automation has been perceived as a remedy and therefore widely discussed. As caseworkers have to work with limited information as well as limited processing capacities, they will have to satisfice for deriving appropriate decision on how to handle individual cases (Tummers et al., 2015). Which case needs more attention, which case will have no trouble in solving the particular situation? Algorithm-based decision-making support tools are ideally supposed to provide a solution to process larger amounts of data to make better decisions. However, the role of digital tools in the context of street-level bureaucracy is a topic of dispute. Buffat (2015) summarizes the discussion using two hypotheses: the enablement and curtailment hypothesis. The former emphasizes the opportunities to automatically process easy cases that require little professional expertise but would normally still bind a substantial number of resources. Hence, by relieving caseworkers of such cases, they are able to focus on more critical or complex cases. The curtailment hypothesis, however, takes a critical stance that digitalization is often accompanied by standardization which in turn reduces discretion that is critical for effective implementation of policies.

This conflict becomes even more critical when putting in the context of AI-induced technologies in which algorithms are often too complex for the caseworkers to comprehend. This may lead to three alternative reactions to algorithm-based decision-making support systems. First, caseworker might lack the trust in the respective tool due to a “black-box effect” (Castelvecchi, 2016). If not forced to use the tool, caseworkers might find workarounds or simply not use the tool purposefully (Gillingham

& Humphreys, 2010). Second, caseworkers may trust the tools results, suggestion, or advice more than their own reasoning or simply take the tool's result for granted. This phenomenon might especially be prevalent with caseworkers that lack experience (Assadi & Lundin, 2018). Third, and the best-case scenario, both caseworkers and the algorithm-based support tool live work complementary as caseworkers will use the tool as another source of information for especially critical or vague cases.

For our specific case setting of unemployment counselling, we assume that the risk-assessment tool will be able to effectively and efficiently direct attention to cases that are more in need of attention. Thus, caseworkers will spend more time on counselling critical cases that might have a harder time finding a new job. Furthermore, caseworkers might be able to better personalize their counselling efforts so that they can identify shortcomings in their clients' competences and suggest the appropriate measures to remedy these shortcomings. Hence, we formulate the following hypotheses:

> *H1: The use of the tool differentially impacts the number of counseling sessions per month conditional on the tool recommendation.*
> *H2: The use of the tool differentially impacts the number of additional courses taken by unemployed members, conditional on the tool recommendation*

Overall, the introduction of such an algorithm-based decision-making support tool is supposed to increase the organization's effectiveness by supporting its caseworkers. In the case of unemployment counselling, we would expect that clients will have an easier time returning into new work – especially if they are identified as critical cases.

> *H3: The use of the tool negatively impacts the time needed for unemployed to return to work.*

While these tools are primarily used for informing the caseworker, they may also affect how clients perceive their situation and measures that are derived from such tools. Several studies have

examined how citizens may view algorithm-based or AI-induced technologies as potential threats to equality (Andrews, 2019; Busuioc, 2020), but also as potential solutions to decrease discrimination (Miller & Keiser, 2021). As our case setting emphasizes the role of co-production – whether unemployed will find a new job is primarily up to their own actions – self-reflection may play a critical role. If clients identify themselves as easy cases that will have little trouble finding a new job, being told that this might not be true will trigger resistance due to cognitive dissonance (Festinger, 2001). However, if the assessment is supported by an algorithm-based support tool, this 'reality shock' might be easier to accept as the information is (seemingly) not only based on the personal assessment from the caseworker. Hence, algorithm-based decision-making support tools may be seen as a more objective adviser compared to the job consultant.

H4: Clients with high self-efficacy are more likely to deny special service provided.

H5: The use of the tool reduces the effect from H4.

Lastly, the interaction itself during a counselling session may affect how the algorithm-based decision-making tool is perceived. The tool is not only a potential black box for the caseworkers, but also for the clients. Thus, it may be critical how effectively caseworkers are able to transparently use the tool and explain its nature and results to the clients. We would expect that if caseworkers are successful at translating the tools implications, it may be easier for clients to accept surprising results that conflict with their self-image. Therefore, reducing the black box effect may encourage clients to accept advise based on the tool.

H6: Informational and procedural justice moderates the effect of H4.

Methods and Data

To address these hypotheses, we conduct a field experiment in a large Danish unemployment fund. Danish unemployment insurance funds are predominantly run by trade unions, and thus private non-profit associations with a double role as both policymakers and policy takers (Freedland, 2007). They are representatives in labor market policy boards, agencies and committees while simultaneously

tasked with the responsibility of implementing the policy. There are therefore also responsible for surveying and guiding unemployment insurance recipients' job search activities and sanctioning any instances of non-compliance.

While decision-making support tools have been implemented in numerous other funds – often using a similar tool called STAR (2021)– our respective fund decided to develop and introduce a risk assessment tool of their own. This provides us with a unique opportunity to investigate the development and implementation process. Of particular interest in this study is a field experiment connected to the rollout process.

In the unemployment insurance fund, each newly unemployed individual is invited for a meeting with their job counsellor in which the job counsellor assesses their job profile, and prospective plans for future employment. For the field experiment, we randomly assign half of the fund's 65 local departments to a treatment group in which the tool will be implemented as part of their normal job counseling process over a three-month phase.[1] In the treatment group, each individual will – based on their consent – let the tool assess their risk of long-term unemployment prior to the first consultation. This will provide the job counsellor with a score indicating whether or not the individual is at risk of long-term unemployment to guide their subsequent job consultation.

To assess the impact of the tool, we use both survey and registry data. The survey data is based on a survey that is automatically sent to *all* individuals in both control and treatment group a week after their first consultation. This allows us to compare how clients in both control and treatment groups perceive the consultation process with the only difference between them being whether or not their first consultation is (partly) based on the algorithmic assessment of their risk of long-term unemployment. We measure the individual experience of the consultation process, as well as attitudinal and motivational factors that may impact the effectiveness of these counseling activities. We combine these measures with registry data that enables us to track the changes in unemployment status, educational activities, and the like.

[1] As the tool will only be used on newly unemployed individuals during their first job consultation at the unemployment insurance office, the duration of the treatment phase depends on how many enters unemployment as well as a power analysis [to be conducted].

Prior to the official rollout, we conducted interviews and participant observations in several test groups that were used to inform the general implementation process in the project. This rich qualitative data is used in order to underpin the discussion of our findings.

Specifically, the following variables are measured in this study:

Use of consulting tool: The treatment group will be asked to use the newly developed consulting tool that assesses the client's risk of long-term unemployment.

- Job search intentions and behavior
    - job search self-efficacy
    - job search clarity
    - job search channels
    - job search intensity
    - expected length of unemployment
- Perception of counseling
    - locus of counseling,
    - amount of counseling
    - level of control
    - quality of counseling
    - procedural and informational fairness
- Trust
    - trust in counseling, counselor, and fund

Registry Data

- administrative data on employment behavior
- gender
- age
- section
- branch/industry
- municipality and region
- data on sanctions (type of sanction, time of last sanction and numbers of sanctions since given date)
- meetings (type of meetings, time of last meeting and number of meetings since given date)

The official rollout is scheduled for January 2022. However, in the following section we provide first insights from the interviews and participant observations.

First Results from Pretest

The declared goal of the introduction of these risk assessment tools is to efficiently use existing resources in welfare services, particularly the unemployment sector. While this is no new ideal in the paradigm of the "activating welfare state" (Arts & Van Den Berg, 2019; Dingeldey, 2007), algorithmic decision-making tools are considered a new opportunity that goes beyond professional discretion enacted by the caseworkers. Accordingly, clients that are able to handle themselves and their own cases should be left alone as consultation and training efforts are not needed and may even have negative effects. Rather, consultation efforts should focus on clients in need. However, the identification of what is considered to be *an easy case* may not always be as evident as one might assume. While proxies, such as education, gender, or age, may serve as useful heuristics used by experienced job counsellors, it is quite possible that potential risks of unemployment may be overlooked or falsely attributed. Hence, these decision-making tools have been introduced to complement caseworkers' professional expertise. Our respective unemployment fund decided to develop an assessment tool that is self-sufficient regarding necessary data. Hence, the tool only uses data already available to the fund. Therefore, a tool used by various other funds has been rejected based on this requirement. The implemented tool uses logistic regression to assess the odds of becoming long-term unemployed based on various characteristics, e.g., age, gender, previous unemployment episodes, region, and trade. The individual coefficients are aggregated and displayed to the caseworker in the form of traffic lights to facilitate the interpretation.

From the get-go, this tool has been explicitly framed as a support tool that is supposed to provide caseworkers with additional processing abilities so that the tool is not considered as a threat for replacement. While this leads to a general acceptance of the tool, still some caseworkers feel their professionalism being challenged. Overall, caseworkers hoped that the tool could serve as "an eye-opener" for vulnerable clients as all members of the fund tend to be (too) optimistic with regard to their outlook and future. Thus, the tool could serve as a *legitimizing objectifier* that provides a seemingly objective measure for long-term unemployment risk.

However, first insights from participant observations indicated what little role this tool plays in first encounters. Normally, the purpose of these first encounters is to introduce newly unemployed to the bureaucratic system they have joined. They get informed about their rights but also obligations, as

well as the processing procedures they may encounter in the next weeks and months. Caseworker even have a checklist of points that they are supposed to address in the first encounter, although some caseworkers stretch them over several encounters. Still, clients are generally flooded with information which may inhibit their ability to process what is happening. The assessment tool itself might often be perceived as “just on information among much more”. However, in few cases in which clients received a low-risk score, they would evidently feel empowered and reassured.

However, as the tool’s purpose is to primarily inform the caseworker, it is more important to address how they interacted with it. From our first observations, we could see that several caseworkers downplay the role of the risk assessment as “just the statistics”. Quite often, they would present themselves as the person in charge, making sense of the results, and as the professional that will guide their way. Thus, caseworkers try to distance themselves from the tool and try to form an alliance with the client. However, at the same time it became apparent in various cases that the level of mastery of this tool was still quite low. Caseworker would find it difficult to translate the information to the clients. For example, they would complain to the client that main factors incorporated in the risk assessment, such as gender or residence, cannot be changed that easily if at all. Moreover, caseworkers would claim that gender plays no role in their risk-assessment, much in contrast to the assessment tool. While this transparent use of the tool is likely to be beneficial for the client’s acceptance, the inability to explain it may have the opposite effect. This may be due to the very early phase these observations have conducted in. As a consequence, caseworkers were still trying to get used to the tool and its implementation in the counselling process.

These initial difficulties also showed in a case in which the caseworker misinterpreted the result from the risk assessment. Obviously puzzled by the gap between the tools result and their personal assessment, they would voice their confusion explaining their standpoint and providing justifications based on their impressions from the discussion. Eventually the caseworker overrode the tools prediction (which was actually in line with her own). Still, this case illustrates how professionals and decision support tools may clash in the heat of service encounters. In most cases, the tool’s and the caseworker’s assessment would align. However, it is especially those cases that inform us about the professional challenges that such tools may bring. In another case, the caseworker also overrode the

tool's assessment because of the client's performance during the conversation. The caseworker was not convinced by the level of motivation to make an effort displayed by the client and her lack of vocational education. Both factors led the caseworker to a different assessment but are not included in the risk assessment. This example emphasizes how professional discretion plays an important role in service encounters despite being informed by algorithmic support tools.

Finally, some caseworkers would perceive considerable stress from having to use the tool in a counselling session that is already packed with required information. This is also aggravated by the required GDPR signing process prior to the tool use, that is considered to be burdensome, taking away additional time, and also inducing mistrust among clients as the tool is unknown to them at that point.

Overall, the test phase of the tool's implementation indicates a complex, yet miniscule effect on counselling encounters. However, these inferences are based on interviews and participant observations alone. Additionally, the pilot tests are explicitly designed to identify mentioned issues. Hence, the full rollout may account for these shortcomings already.

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