Structuring the scattered literature on algorithmic profiling in the case of unemployment through a systematic literature review

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Abstract

Purpose – This article examines the overlooked literature on algorithmic profiling in public employment services (APPES) in the field of public administration. More specifically, it aims to provide an overview and connections to identify directions for future research.

Design/methodology/approach – To understand the existing literature, this article conducts the first systematic literature review on APPES. Through inductive coding of the identified studies, the analysis identifies concepts, and themes, and the relationships among them.

Findings – The literature review shows that APPES constitutes an emerging field of research encompassed by four strands and associated research disciplines. Further, the data analysis identifies 23 second-order themes, five dimensions, and ten dynamic interrelationships, thus suggesting that the practices and effects of algorithmic profiling are multidimensional and dynamic.

Originality – This literature review contributes by connecting the existing literature across different research approaches and disciplines.

Research limitations/implications – The findings demonstrate the importance of future research on APPES undertaking a holistic approach. Studying certain dimensions and interrelationships in isolation risks overlooking mutually vital aspects, resulting in findings of limited relevance. A holistic approach entails considering both the technical and social effects of APPES.

Keywords Algorithmic profiling, artificial intelligence, public sector, unemployment, systematic literature review

Paper type General review

1. Introduction

Although the field of artificial intelligence (AI) in the public sector is still "in its infancy", public governance increasingly applies AI (Wirtz *et al*., 2019, p. 608; Zuiderwijk *et al.,* 2020). AI's popularity is growing in part because of its effects on policymaking (Kolkman, 2020; Zuiderwijk *et al.,* 2020). For example, AI applications can improve the cost efficiency of service delivery (Desiere and Struyven, 2020, p. 1). A prominent cause for the recent attention of AI is advancements in machine learning techniques (Wirtz *et al*., 2019, p. 1), which enables computers to learn from data rather than relying on predefined rules; thus, computers' learning ability evolves through experience (The Royal Society, 2017).

One particularly relevant AI application in the public sector is algorithmic profiling (Angwin *et al.*, 2016; Crawford, 2021; Desiere *et al*., 2019; Eubanks, 2018; for AI definitions, see Agrawal *et al.*, 2018; Russell and Norvig, 2010, p. 2; Wirtz *et al*., pp. 599–601). However, studies and reviews of AI use in the public sector have overlooked algorithmic profiling concerning unemployment (de Sousa *et al*., 2019; Valle-Cruz *et al*., 2020; Wirtz *et al*., 2019; Zuiderwijk *et al*., 2021). Although several studies have provided valuable overviews of this literature on algorithmic profiling and unemployment (Desiere *et al*., 2019; Griffin *et al*., 2020; Körtner and Bonoli, 2021; Loxha and Morgandi, 2014), these studies are scattered across different areas and have not systematically reviewed the literature, nor are they academic articles.

Therefore, based on these gaps, this article conducts the first systematic review of the literature on algorithmic profiling in public employment services (APPES). This review aims to connect the literature from different disciplines and provide directions for future research (Grant and Booth, 2014, p. 95). As this article demonstrates, research on this topic is increasing, making literature reviews worthwhile to pursue (Webster and Watson, 2002). Further, algorithmic profiling through predictions of future unemployment can influence recipients' social security or insurance payments and service provision and can discriminate against the unemployed (Bannister and Connolly, 2020, p. 483; Zhao, 2021, pp. 1–2). Consequently, this article aims to deepen our understanding of this emerging research field with real-world implications.

This article understands algorithmic profiling as "a method of inferential analysis that identifies correlations or patterns within datasets that can be used as an indicator to classify a subject as a member of a group" (Mann and Matzner, 2019, p. 1). Following this definition, algorithmic profiling in this article includes both regression-based profiling and AI-based profiling (Breiman, 2001; Desiere and Struyven, 2020). Examples of implementations of algorithmic profiling of the unemployed include the 1993 US initiative, 'Worker Profiling and Reemployment Services' (WPRS), which uses logistic regression to predict if unemployment insurance (UI) claimants exhaust their 26-week UI entitlements (Wandner, 1997). Another example is the Australian 'Job Seeker Classification Instrument' (JSCI), a logistic regression model launched in 1998 that predicts long-term unemployment (exceeding 12 months) (Desiere *et al*., 2019). More recent examples of AI-based profiling models include a random forest algorithm in Flanders (Belgium), which predicts long-term unemployment (exceeding six months) (Desiere and Struyven, 2020). For further examples of APPES, see section 3.2 in this article and Desiere *et al*. (2019, p. 12) and Griffin *et al*. (2020, pp. 5-6).

The article proceeds as follows: Section 2 clarifies the inclusion criteria, the search protocol of this review, and the data analysis strategy using the Gioia methodology (Gioia *et al*., 2013). Section 3 first gives an overview of the literature through four categorisations and clarifies the different literature strands. It then presents the data analysis of numerous first-order concepts, 23 emerging second-order themes, and five aggregate dimensions. Third, Section 3 clarifies the content and the dynamic relationships of the emerging themes and dimensions. Figure 3 illustrates this data analysis. Finally, Section 4 discusses the article's contributions, limitations, and implications for future research.

2. Methodology

This article identifies literature on APPES using Scopus and Google Scholar, chosen because of their broad coverage. The literature identification uses the following inclusion criteria: studies or discussion of APPES limited to English-language peer-reviewed articles, conference papers, journal comments, research, policy, discussion papers and reports, and book chapters. Figure 1 depicts the search protocol based on Page *et al*. (2021), which is subsequently clarified.

Figure 1. PRISMA flow chart of the search protocol

[Insert Figure 1 here]

The Scopus search used the following search string: (TITLE-ABS-KEY (profiling OR screening OR targeting OR "support system" OR "assessment system" OR "assessment tool") AND TITLE-ABS-KEY (unemploy* OR "labour market" OR "job seeker*" OR "welfare recipient" OR "employment service" OR "social security" OR "work-fare" OR "social policy" OR "employment barrier")), limited to only relevant fields of research. Upon trying different Google Scholar search strings, this article found the following search string most relevant: (profiling AND unemployment) AND (algorithmic OR statistical). The screening steps excluded studies that did not examine the topic criteria. Otherwise, studies proceeded to further examination. Webster and Watson (2002, p. xvi) recommended going backwards in the literature upon identifying literature.

The search protocol identified 125 studies, consisting of 57 peer-reviewed journal articles; 43 research, policy, and discussion papers and reports; 15 book chapters; nine conference papers;

and one journal comment. In addition to the articles and conference papers, the grey literature supplements the sparse academic literature and provides additional findings and insights. Existing overviews (cf. introduction) confirm this article identifies more academic literature than has previously been found.

2.1 Coding Strategy

The literature coding strategy categorises the document type and publication year, the lines of studies and patterns of empirical findings, the research disciplines of the articles, the conference papers and the journal comment, and the number of case studies per country (see Section 3).

Second, the data analysis uses the Gioia methodology (Gioia *et al*., 2013). This methodology enables a systematic approach to develop new concepts and articulating grounded theory that aims to “bring qualitative rigor to the conduct and presentation of inductive research” (Gioia *et al*., 2013, p. 1). This data analysis first generates numerous first-order concepts. A first-order concept is a “more general, less well-specified notion capturing qualities that describe or explain a phenomenon of theoretical interest” (Gioia *et al*., 2013, p. 16). Second, data analysis categorises the first-order concepts into second-order themes. Third, the data analysis distils the second-order concepts into aggregate dimensions, which results in the data structure (Gioia *et al*., 2013, p. 20; see Table 4). The use of NVivo and Excel assisted this process.

Figure 2 presents the model generated from the data analysis. This figure illustrates the dynamic interrelationships between the emergent themes and dimensions (Gioia *et al*. 2013, p. 22). This article thus produces a dynamic inductive model that provides “an avenue not only for theory development but also for bringing together approaches that should not have been treated as strange bedfellows in the first place” (Gioia *et al*., 2013, p. 25; see Section 3.2).

3. Findings

The first section provides four categorisations of the literature and thus gives an overview. The second section presents the data structure and clarifies the themes and dimensions' content and interrelationships.

3.1 Mapping the Literature

Figure 2 presents the distribution of the 125 identified studies categorised by publication year and document type.

Figure 2. Studies per year and document type

[Insert Figure 2 here]

Figure 2 shows increasing research interest in the topic of APPES. The total number of articles peaked in 2020 and 2021, and studies in total peaked in 2021.

Table 1 presents the lines of studies and patterns of empirical findings in five categories.

Table 1. Categorisation of lines of studies and patterns of empirical findings

[Insert Table 1 here]

This article clarifies the five categorisations in Table 1 after presenting the research disciplines of the articles, conference papers, and the journal comment in Table 2 and examines these two tables together. This shows that the literature encompasses four strands of literature and that the research disciplines vary in two of these strands.

Table 2. Research disciplines for academic literature

[Insert Table 2 here]

The first strand of literature develops and evaluates profiling models or compares the performance of such models. This strand of literature encompasses three research disciplines.

The first set of articles that develop and evaluate profiling models occurs in the disciplines of economics and statistics (e.g., O'Connell *et al*., 2012; Wijnhoven and Havinga, 2014), public administration (Desiere and Struyven, 2021), and sociology (Kelly *et al*., 2012). The next set of articles that develops and evaluates profiling models appears in psychology (e.g., Houssemand *et al*., 2014). The third set of articles appears in the discipline of computer science (e.g., Boskoski *et al*., 2021; de Troya *et al*., 2018). Finally, the articles comparing the performance of profiling models vary among the disciplines of economics (Lechner and Smith, 2007; Staghøj *et al*., 2010), computer science (Kern *et al*., 2021; Zhao, 2020), and public administration (Peck and Scott, 2005).

The next strand of literature politicises profiling and its power dynamics. It encompasses five research disciplines, the first being the discipline of sociology (e.g., Caswell *et al*., 2010; Henman, 2004). The second is political economy (Grundy, 2015). The third strand is public administration (e.g., Assadi and Lundin, 2018). The fourth is computer science (Allhutter *et al*., 2020; Flügge *et al*., 2021; Møller *et al*., 2020; Petersen *et al*., 2021) and information science (e.g., Kuzjemski and Misuraca, 2020). The fifth is communication (Andreassen *et al*., 2021).

The next strand of literature describes and clarifies profiling models' workings. The articles containing this line of study fall within the disciplines of economics (e.g., Behncke *et al*., 2009; Harmon *et al*., 2014; Wandner, 2008), public administration (Wandner, 1997), and psychology (Englert *et al*., 2014). This strand includes research, policy discussion papers and reports, and book chapters.

The fourth strand of literature compares experiences internationally and with different profiling models. These studies are research, policy discussion papers, or reports published by international organisations such as the European Commission (e.g., Barnes *et al*., 2015), ILO (Corbanese and Rosas, 2014), the OECD (e.g., Desiere *et al*., 2019), and the World Bank (Loxha and Morgandi, 2014). These studies typically provide policy recommendations. The remaining studies in this strand are book chapters. Finally, the studies that minimally discuss profiling do not constitute a strand of literature on their own.

Table 3 shows the number of case studies per country for all reviewed studies. For instance, a case study examines the feasibility of developing a profiling model or examines the effects of a deployed profiling model in a specific country.

Table 3. Count of case studies per country

[Insert Table 3 here]

Table 3 shows that the USA is the country where most case studies of APPES have been conducted, followed by Australia and Denmark with an equal tally. The USA and Australia are pioneers of statistical profiling, which might explain his distribution. In the case of Australia, APPES was used to support the privatisation of the employment sector (Considine *et al*., 2022). Denmark deployed the "Jobbarometer" in the mid-2000s (Caswell *et al*., 2010) and a decision tree algorithm since 2015 that, however, was discontinued in February 2022 (Beskæftigelsesministeriet, 2022).

Considering the included countries in Table 3 more broadly, the use of APPES relates to different types of welfare regimes (see Greve, 2017, p. 28). In liberal welfare regimes (Australia, Ireland and the USA), the use of APPES is compulsory for both jobseekers and caseworkers, whereas in the Nordic welfare regime, the use of APPES is voluntary for caseworkers (Denmark and Sweden) and for jobseekers (Denmark) (Desiere *et al*., 2019, p. 12). In the continental and the Eastern

European welfare regimes, the degree of voluntary and compulsory differs for caseworkers and jobseekers, respectively (Desiere *et al.*, 2019, p. 12). The use of APPES also relates to street-level bureaucracy. Countries in the liberal welfare regime deploy fully automated decision-making or system-level bureaucracy. In contrast, the Nordic, continental and Eastern European welfare regimes deploy a mixture of street-level bureaucracy and screen-level bureaucracy (Bovens & Zouridis, 2002; Desiere *et al.*, 2019, pp. 20-21; Roehl, 2022, p. 42). Additionally, the GDPR prohibits automated profiling in all European Union member states (Zhao, 2020).

3.2 Data Analysis of the Literature

The following section discusses and clarifies the data structure. Table 4 shows the resulting data structure consisting of first-order concepts and example references, 23 emerging second-order themes encapsulating these concepts, and five aggregate dimensions encapsulating the themes.

Table 4. Data structure

[Insert Table 4 here]

3.2.1 Policymakers

The first dimension, *policymakers*, concerns policymakers' drivers, considerations, and objectives applying profiling through public employment services (PES). This dimension refers to national (Mozzana, 2019), state-level (Wandner, 2008), regional (Frölich *et al.*, 2003), and municipal policymakers (Rice, 2017), as well as international and national legal institutions (Dencik and Kaun, 2020; Kuzjemski and Misuraca, 2020). As described in Table 4, policymakers have various profiling drivers, for instance, ensuring scarce resources targeted toward jobseekers most in need and delivering intensive services before long-term unemployment occurs (O'Connell *et al.*, 2012, p. 136). The "datafication" of welfare states and the consideration that profiling enables a more objective and neutral assessment than caseworkers' discretion further drive the use of profiling (Dencik and Kaun, 2020; Marston, 2006, p. 91).

There are also various profiling considerations, such as choosing the target group of jobseekers and selecting profiling criteria (Boskoski and Boshkoska, 2020, p. 5; Körtner and Bonoli, 2021, p. 7). The choice of profiling type depends on several factors, such as "governance- and policy-related factors", where a more extensive "scope of benefit delivery" increases the "demand for more-complex profiling systems" (Loxha and Morgandi, 2014, pp. 16–17). Finally, using profiling aims to deal with existing issues in the unemployment system. For instance, caseworkers being "too soft" (Caswell *et al*., 2010, p. 396), treating all unemployed alike (O'Connell et al., 2012, p. 137), or mitigating "inefficient, understaffed and unfit" PES (Kuzjemski and Misuraca, 2020, p. 7).

3.2.2 Data

The second dimension, *data*, concerns the pre-processing of profiling data and describes the complexity of acquiring data of adequate quality. Wijnhoven and Havinga (2014), for example, illustrated the laboured development of "The Work Profiler" tool, including literature, cross-sectional, and longitudinal studies, before identifying 11 predictive factors (p. 746). In this context, Matty (2013) noted that the purpose of profiling development is to "identify the most efficient predictors of future LTU" rather than the "most important factors behind LTU" (p. 8). The collection of data precedes the profiling development. Currently, the dominant data collection methods are administrative data and questionnaires (Desiere *et al*., 2019, p. 12), although advances in machine learning increase the availability of big data (Kern *et al*., 2021, p. 2; see de Troya *et al*., p. 2). Moreover, Matty (2013), for instance, found that the best performance included a mix of "attribute data, administrative data, and attitudinal data" (p. 1). Griffin *et al*. (2020) noted that "profiling rarely includes unemployed people's needs or aspirations" nor job quality metrics (p. 10).

The data quality affects the performance of profiling. Data quality consists of "the data integrity, accuracy, and collection process" and "is of utmost importance to the success of any profiling model" (Boskoski and Boshkoska, 2020, p. 5). Poor data quality can lead to incorrect predictions of jobseekers, also known as deadweight (O'Connell *et al*., 2012, p. 138) or inadequate advice to caseworkers (Grundy, 2015, p. 59). Profiling models require recalibrations to sustain their performance (Corbanese and Rosas, 2017, p. 31).

Profiling models used in PES often rely on other organisations to develop profiling models, as illustrated by the Dutch Institute for Employee Benefit Schemes (Wijnhoven and Havinga, 2014). Besides national departments and agencies, research institutes (O'Connell *et al*., 2012), researchers affiliated with universities (Rosholm *et al*., 2004), or external service providers (Desiere *et al*., 2019) can conduct the development.

Finally, data can also be personal (see Allhutter *et al*., 2020, p. 6) or sensitive personal data character (as in the GDPR). Personal data can, according to developers, represent the harsh realities of structural labour market discrimination and thus be included (Allhutter *et al*., 2020, p. 7). Quite the reverse, personal data may not comply with European and local anti-discrimination laws (Niklas *et al*., 2015, pp. 20–23), leading to the eventual discontinuation of a profiling tool, such as occurred in Poland (see Kuzjemski and Misuraca, 2020, p. 8). However, excluding sensitive personal data such as origin "does not necessarily reduce discrimination" because other variables correlate with origin (Desiere and Struyven, 2020, p. 14). Downstream discrimination in unemployment profiling can be positive—for example, services reserved for high-risk jobseekers—or negative, if perceived as burdensome (Desiere and Struyven, 2020, p. 15).

3.2.3 Profiling Models

The third dimension, *profiling models*, concerns engineering profiling models, evaluating their performance, and dealing with subsequent challenges such as bias and fairness, applied in the PES.

Various profiling models typically predict long-term unemployment and employ logistic regression (Desiere *et al*., 2019, p. 12). They include various performance metrics such as precision, sensitivity, specificity, and area-under-the-curve (AUC) (Zhao, 2020), pointing to the problem of accounting only for the accuracy metric (e.g., Desiere *et al*., 2019, p. 12) or only for the statistical significance of predictors (O'Connell *et al*., 2012).

Although AI-based profiling models, such as a random forest model, have not yet been widely applied, Desiere and Struyven (2020) consider them "the next step in the development of statistical profiling models" (p. 2). AI-based profiling is potentially superior to regression-based profiling because it can be "updated continuously", include "many more explanatory variables", and generally predicts more accurately (Desiere and Struyven, 2020, pp. 3–15; see also Zhao, 2020, p. 14). However, Desiere and Struyven's (2020, p. 3) finding of an accuracy-equity trade-off holds for both AI-based and regression-based profiling (i.e., algorithmic profiling), which also holds for the performance-complexity trade-off (see de Troya *et al*., 2018).

In addition, engineering a profiling model and its output variable can require the input of involved stakeholders. For example, Møller *et al*. (2020) showed how data scientists and caseworkers negotiate value metrics, shifting the focus from individual profiling to "lay time" in the organisation (p. 10).

Only a few studies have examined caseworkers' discretion *vis-à-vis* statistical treatment rules in allocating the unemployed to active labour market programs. Both Lechner and Smith (2007) and Staghøj *et al*. (2010) suggested that introducing a statistical treatment rule, rather than only relying on caseworkers' discretion, reduces the average duration of unemployment (see also Desiere *et al*., 2019, p. 15). Harmon *et al*. (2021) provided "the first attempt to combine statistical profiling with an econometric policy evaluation of an information treatment for unemployed workers," and their results indicate that profiling is "a promising way to speed up unemployment exit" (p. 147). However, according to Barnes *et al*. (2015), profiling tools lack evidence concerning their effectiveness and support of labour market (re)integration support for jobseekers.

When engineering profiling models, developers may encounter technical issues. The so-called "black box problem" indicates that it is "not always possible to scrutinize the algorithm or statistical method underlying the profiling tool that is being used" (Desiere *et al*., 2019, p. 4). To mitigate this problem, Zhao (2020) used SHapley Additive exPlanations (SHAP) to explain "how each feature, or a pair of features contributes to the prediction", thus providing a better understanding of what contributes the most to the predicted risk (p. 14). Further, Zhao (2020, pp. 7–14) used the Aequitas toolkit to audit bias and discrimination, finding that the particularly developed algorithm "fails the bias audit", which suggests researchers "should aim to mitigate bias before implementing" real-world profiling models (p. 14). Similarly, Kern *et al*. (2021) called for "rigorous auditing processes" before implementation, highlighting how "different classification policies have very different fairness implications" (p. 1). Moreover, "determining the classification threshold cannot be done without consulting a country's socio-institutional context", and policy and statistical experts should accordingly cooperate (Kern *et al*., 2021p. 23).

3.2.4 Public Employment Services

The fourth dimension, *public employment services*, concerns the provision of services to jobseekers using profiling, whether piloting (e.g., Peck and Scott, 2005), implementing (Wandner, 2008), or operating daily (Assadi and Lundin, 2018). A PES may be composed of several suborganisations, such as Centrelink in Australia (Desiere *et al*., 2019, p. 22), as well as comprise different levels within one organisation (Pultz, 2016).

There are various profiling drivers for PES (Desiere *et al*., 2019, p. 7; Pietersen, 2017), as well as various implementation choices and challenges; in addition, there are various specific organisational functions profiling can serve (described in Table 4). For instance, Matty (2013) noted that "operational accuracy", that is, effective unemployment interventions, is mutually as important as accurate predictions (p. 3). Similarly, Grundy (2015) found that caseworkers' questions concerning data use and privacy "eventually proved to be the most formidable obstacle to implementation" in the case of the Canadian SOMS-model (p. 61).

References such as Barnes *et al*. (2015, p. ii) have underscored the involvement of caseworkers in profiling endeavours. They are crucial to the data collection that feeds into profiling models and predictions. For instance, Petersen *et al*. (2021, pp. 17–18) found that caseworkers can hold a moral unwillingness to provide data to the profiling system—caseworkers' informal classifications could conflict with the formal classifications applied by the job centre. Moreover, Boskoski and Boshkoska (2020) stated that accurate prediction "hinges on skilled caseworkers providing the correct information on the jobseekers" (p. 5).

The more tension-filled aspects concern the interactions between managers and caseworkers and between caseworkers and jobseekers. Managers, for instance, perceive the "rationalization of frontline service delivery" as crucial to assist caseworkers' encounters with jobseekers and encourage a greater sense of responsibility for the unemployed to their situation (Assadi and Lundin, 2018; Grundy, 2015, p. 56; Pultz, 2016). This rationalisation, i.e., profiling, affects caseworker discretion and might relate to caseworkers' experience. Assadi and Lundin (2018) found that caseworkers with a higher tenure, especially males, tended to follow the profiling score or "policy signals to a lesser extent" because of acquired experience (p. 154). On the contrary, some younger PES caseworkers considered profiling tools helpful in leaning against and strengthening their discretional confidence. Zejnilovic *et al*. (2020) found that “although the counsellors could override” the algorithm’s prediction, “the information system’s user interface” demotivated them from doing so (p. 6). Kuzjemski and Misuraca (2020) found that “lack of time to ponder its details; fear of repercussions from the supervisors; and a belief in the objectivity of the process” were reasons caseworkers did not challenge the profiling algorithm (p. 8). McGuinness and Kelly (2020) stated that the current Irish profiling tool “is arguably no longer appropriate” because it posed a high administrative burden on the caseworkers (p. 11).

Moreover, the PES dimension concerns the reasons for the discontinuation of profiling tools. Examples of caseworker resistance include: caseworkers perceiving profiling results as demotivating to jobseekers (Caswell *et al*., 2010, p. 397); caseworkers finding tools useless and untrustworthy (Loxha and Morgandi, 2014, p. 17); or caseworkers either ignoring the tool or being “over-confident in that their own experience [which] clearly dominates any information that a statistical system might provide” (Behncke *et al*., 2009, p. 224). To Behncke *et al.* (2009), profiling poses a dilemma: “When providing no incentives to use the system, caseworkers may ignore or sabotage it. However, severely restricting caseworkers’ discretion crowds out intrinsic motivation and does not exploit the value of the private information of the caseworker” (p. 224).

3.2.5 Jobseekers

The fifth dimension, *jobseekers*, concerns jobseekers’ interactions with PES, their experiences, and the effects of profiling.

Caswell *et al*. (2010) found the use of profiling risked individualising unemployment and reduced complex social problems to “statistical scores and differentiated categories”, which “diminish the capacity to think about unemployment as a collective problem requiring collective solutions” (p. 384). This critique aligns with McDonald *et al*.’s (2003) thought that profiling is a "risk technology" that "both assumes and imposes particular subject identities on unemployed people" and perpetuates neoliberal logic (p. 498).

In terms of experiences, Mozzana (2019, p. 225) showed how overlooking disadvantaged groups counteracts the policy aims of profiling. Moreover, Kuzjemski and Misuraca (2020) claimed that the Polish profiling tool is opaque—"the subject is aware neither of her score nor how certain features determine the final categorisation" (p. 8). The opacity of profiling can pose "a serious hindrance" to the accountability of its creators, exemplified by the omission of "the number of models, model coefficients, and the complete list of error rates/precision" (Allhutter *et al.*, 2020, pp. 13–14). Henman (2005, p. 94) called for greater public transparency of profiling, enabling independent checks and public reporting. Finally, PES has been criticised for invading and challenging jobseekers' right to privacy (Niklas *et al.*, 2015, p. 25). Jobseekers' self-disclosure of information influences model accuracy (Desiere *et al.*, 2019, p. 22).

Based on Table 4 and the preceding discussion of the dimensions and their relationships, Figure 3 summarises these findings in the following model (Gioia *et al.*, 2013, p. 24).

Figure 3. A grounded theory model of the dynamic interrelationships of algorithmic profiling in public employment services

[Insert Figure 3 here]

4. Conclusion and Discussion

The systematic literature review shows that the literature on unemployment profiling constitutes an emerging field of research (Figure 2) scattered across disconnected studies within different disciplines. Specifically, the review reveals that the literature encompasses four main strands demarcated by different research disciplines. The data analysis identifies 23 second-order themes, five dimensions, and ten dynamic interrelationships (Table 4 and Figure 3), thus connecting the reviewed literature. This analysis suggests that the practices and effects of algorithmic profiling are multidimensional and dynamic. This conclusion echoes Allhutter *et al.*'s (2020) argument that profiling is not "a mere technical tool, but rather a socio-technical endeavour both embedding and reinforcing certain socio-political goals" (p. 13).

4.1 Research Contributions

This article contributes to the literature on unemployment profiling by providing an overview and making connections among previous literature. Further, this article brings together "strange bedfellows" by structuring the literature containing different research approaches, research disciplines, and various first-order concepts. In addition, it extends existing reviews with a more literature-specific and comprehensive overview than has been the norm in existing overviews (e.g., Desiere *et al.*, 2019; Griffin *et al.*, 2020; Loxha and Morgandi, 2014). This article enables a strategic research approach when researching APPES and clarification of dimensions and relations.

The identified conceptual model may apply to other profiling domains, such as policing (Eubanks, 2018), or to other AI applications (Wirtz *et al.*, 2019), because the interactions of policymakers, data, algorithms, organisations, and citizens likely affect each other regardless of domain or application (cf. Gioia *et al.*, 2013, p. 25)

4.2 Research Limitations

The present study is not without limitations. First, reviewing only English-language studies excludes relevant literature written in other languages (e.g., Desiere *et al.*, 2019). Employing a grounded theory, which "presumes a level of semi-ignorance or some suspension of belief in the received wisdom of prior work" (Gioia *et al.*, 2013, p. 23), limits the specificity of the identified conceptual model (Table 4 and Figure 3). Narrower (theoretical) scopes could provide more nuanced descriptions and explanations; for example, having a focus on how APPES shapes the different stages in the policymaking cycle (see Kolkman, 2020) or influences caseworkers' artificial discretion (Young *et al*., 2019) or how APPES causes citizens harm of representation and allocation (Suresh and Guttag, 2021). However, the Gioia approach enables structuring the literature across different research areas into a common model.

Moreover, the review includes a considerable amount of grey literature, implying a particular bias favouring applying profiling. However, including this literature augments a field with scarce academic interest. Further, the conceptual model originates from the reviewed literature and does not present a total picture or the reality of profiling. Specifically, other concepts, themes, dimensions, and mutual relations can emerge—particularly from further empirical studies—and the conceptual model is neither final nor conclusive.

4.3 Implications for Practice

This article could remind public decision-makers (i.e., policymakers and managers) to consider algorithmic profiling carefully and holistically. This application promises straightforward cost reductions and more efficient service delivery. However, as mentioned previously, the implementation of profiling may backfire, as illustrated by the many discontinued profiling projects caused by discrimination issues (Kuzjemski and Misuraca, 2020) or facing caseworker resistance (Zejnilovic et al., 2020, p. 6). Therefore, public decision-makers should consider the many aspects and relations, including sensitive variables, emerging fairness issues, caseworker involvement, and jobseeker experiences. Loxha and Morgandi (2014, pp. 7-8) provide an overview of the practical uses of profiling and state that the primary use is client segmentation, which aims to differentiate services based on jobseeker's risk predictions. However, as Barnes *et al*., (2015, p. 93) note, "there is a significant gap in evidence concerning the effectiveness of profiling tools and whether targeting support and resources using this process can be effective in re/integrating individuals into the labour market and supporting sustainable employment outcomes". Moreover, the conducted analysis, do not support, as O'Connell *et al*. (2012, p. 135) states, that profiling "will result in both equity and efficiency gains to Public Employment Services". Thus, according to the present study's findings, public decision-makers are advised to consider the use of APPES holistically and approach it carefully as such. Practitioners must also bear in mind that the use of APPES constitutes an emerging field of research, and further studies are needed to assess the suitability of APPES. Furthermore, even if there is scientific evidence, say caseworkers' doubtful ability to assign services to jobseekers (see Lechner and Smith, 2007, p. 22), public decision-makers face local organisational challenges and obstacles (Pietersen, 2017)

4.4 Implications for Future Research

This article's significant implication is that future researchers need to examine APPES holistically. Specifically, studies that overlook certain dimensions and interrelationships or study them in isolation may prove of limited relevance, overlooking other vital aspects or, in the worst case, harming users. The provided overview may reduce such issues in future research.

On the one hand, for researchers involved in the development and evaluation or comparison of profiling models, the present study suggests it is important to consider the social effects of profiling (i.e., the policymakers, PES, and jobseeker dimensions). The idea that the data quality is of utmost importance to profiling should consider mutually vital aspects such as caseworker involvement and resistance (cf. Table 4). Moreover, Kern *et al*. (2021) stated, "To implement a statistical profiling approach, in reality, one needs to consider many design and policy decisions beyond pure technical details of the statistical prediction model" (p. 23). On the other hand, the examination suggests that literature that politicises the use of profiling and describes the workings of profiling models needs to give more attention to the technical aspects of algorithmic profiling (i.e., the data and profiling models dimensions), including how bias and fairness audits can mitigate downstream discrimination. For these reasons, this article recommends more studies employing a cross-disciplinary approach to provide more holistic understandings.

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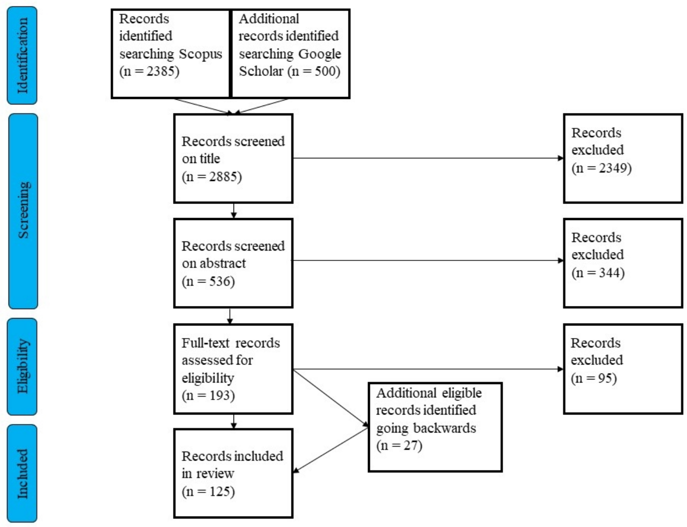

Figure 1. PRISMA flow chart of the search protocol

338x190mm (96 x 96 DPI)

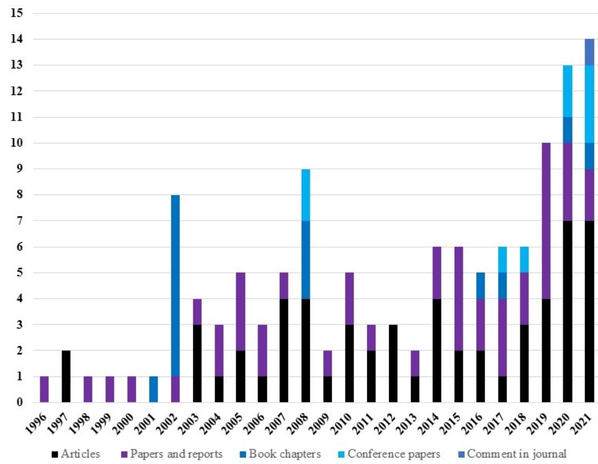

Figure 2. Studies per year and document type

338x190mm (96 x 96 DPI)

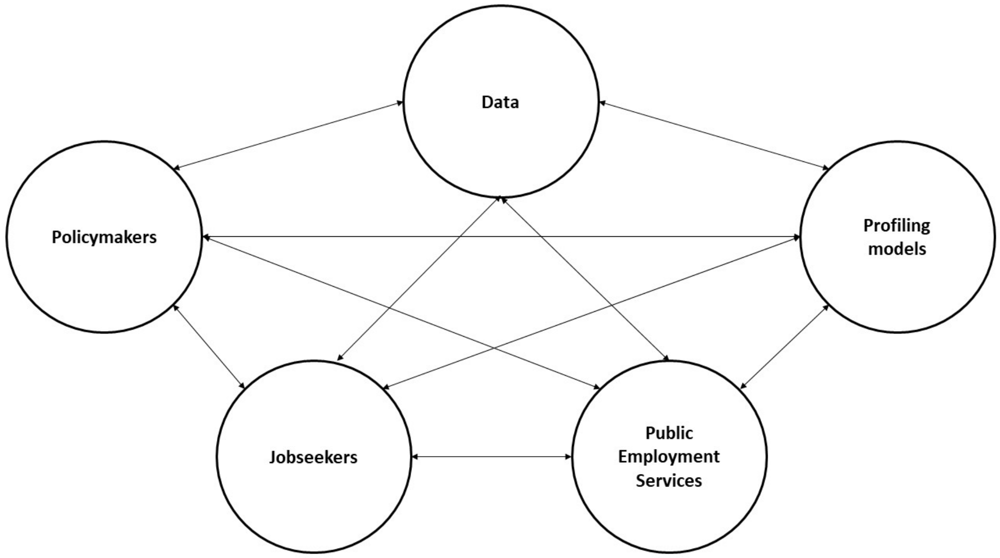

Figure 3. A grounded theory model of the dynamic interrelationships of algorithmic profiling in public employment services

338x190mm (96 x 96 DPI)

Table 1. Categorisation of lines of studies and patterns of empirical findings

Categories	Count
Develop and evaluate or compares the performance of profiling models	34
Politicises the use of profiling models and renders power dynamics visible, e.g., calls objectivity and neutrality into question	29
Describe and clarify the workings of profiling models	29
Compares experiences internationally and with different types of profiling models	21
Only discusses profiling as a minor part of a broader examination	12

Table 2. Research disciplines for academic literature

Research Disciplines	Count
Economy and statistics	18
Sociology	16
Computer science and information science	14
Public administration	9
Psychology	8
Political economy	1
Communication	1

Table 3. Count of case studies per country

Country	Count
Azerbaijan	1
Austria	1
Australia	11
Canada	2
Czech Republic	2
Denmark	11
Flanders (Belgium)	2
Germany	2
Ireland	7
Italy	2
Malaysia	1
New Zealand	1
Latvia	1
Luxembourg	3
Poland	5
Portugal	3
Slovenia	1
Slovakia	2
South Africa	1
Switzerland	5
Sweden	1
The Netherlands	4
Tunisia	1
UK (United Kingdom)	2
USA	23
Total	93

Table 4. Data structure

Aggregate Dimensions	2nd Order Themes	1st Order Concepts	Example References
Policymakers	**Profiling drivers**	Government-imposed costs	Wijnhoven and Havinga, 2014, p. 1
		Profiling systems support targeting decisions	Körtner and Bonoli, 2021, p. 7
		Technological and data analysis advancements	Dencik and Kaun, 2020, p. 3
		Neoliberal reform, marketisation, and austerity politics	Allhutter *et al.*, 2020
		External influences such as Covid-19	McGuinness and Kelly, 2020, p. 10
	Profiling purposes	Various types of uses and focuses of profiling	Loxha and Morgandi, 2014, pp. 6-8
		Efficient use of resources	O'Connell *et al.*, 2012, p. 136
		Tailoring services to jobseekers' need	Rice, 2017
	Profiling objectives	Leave practice of treating all unemployed alike	O'Connell *et al.*, 2012, p. 137
		Leave practice of queuing per duration of unemployment	O'Connell *et al.*, 2012, p. 137
		Too soft or too subjective caseworkers	Caswell *et al.*, 2010, p. 396
		Existing issues in unemployment system	Kuzjemski and Misuraca, 2020, p. 7
	Profiling considerations	What unemployment-related phenomenon to target?	Desiere *et al.* 2019, p. 12; Wandner, 2008, p. 17
		Definition of types of unemployment spells	Desiere *et al.* 2019, p. 12
		Which job seekers to target?	Boskoski and Boshkoska, 2020, p. 5
		Compulsory or voluntary tool for users?	Desiere *et al.*, 2019, p. 12
		GDPR compliance	Zhao, 2020
		Balancing efficiency and equity considerations	Desiere and Struyven, 2020, p. 4
		Profiling is more objective and neutral than caseworkers	Andreassen *et al.*, 2021; Marston, 2006, p. 91
Data	**Data acquisition**	Types of data; attribute, administrative, and attitude data, and psychological dimensions	Matty, 2013, p. 1; Wijnhoven and Havinga, 2014, pp. 743-746; Houssemand *et al.*, 2014
		Types of data collection methods	Desiere *et al.*, 2019, p. 12; Kern *et al.*, 2021, p. 2;
		Data costs vs. efficiency	Loxha and Morgandi, 2014, p. 17
	Data quality	The importance of data quality	Boškoski *et al.*, 2021
		The costs of poor data quality	Grundy, 2015; O'Connell *et al.*, 2012, p. 138
		Recalibration of data	McGuiness and Kelly, 2020, p. 12
		Missing but relevant data inputs such as job quality	Griffin *et al.*, 2020
		Biased data	Zhao, 2020, pp. 7-8
	Personal data	The inclusion or exclusion of personal variables	Allhutter *et al.*, 2020, p. 7
		Sensitive data compliance with anti-discrimination laws	Niklas *et al.*, 2015, pp. 20-23
		Data that correlates with personal data	Desirie and Struyven, 2020, p. 14
Profiling Model	**Model engineering**	Determining the output variable and number of target groups	Desiere *et al.*, 2019, p. 12

		Types of profiling models	Boskoski *et al*., 2021; Desiere and Struyven, 2020
		AI-based profiling compared to statistical profiling	Desiere and Struyven, 2020; Zhao, 2020, pp. 12-13
		Identifying the most efficient predictors of future unemployment	Matty, 2013, p. 8
		Negotiating notions of value metrics by the key stakeholders	Møller *et al*., 2020, p. 1; Kern *et al*., 2021
		The black box problem	Desiere *et al*., 2019, p. 4; de Troya *et al*., 2018
		Explainable AI	Zhao, 2020, p. 14
	Model evaluation	Evaluating the accuracy-equity Trade-offs	Desiere and Struyven, 2020, p. 14
		the performance/complexity trade-off	de Troya *et al*., 2018, p. 1
		Statistical profiling compared to caseworker-based profiling	Lechner and Smith, 2007; Staghøj *et al*., 2010
		Evaluation metrics of profiling model performance	Allhutter *et al*., 2020, p. 8
		Econometric policy evaluation	Harmon *et al*., 2021
		Evaluating fairness	Desiere and Struyven, 2020, p. 14
		Auditing models for bias and fairness	Zhao, 2020, pp. 7-14; Kern *et al*., 2021
		Classification policies have different fairness implications [	Kern *et al*., 2021
Public Employment Services	**Organisational drivers**	Budgetary pressures	Desiere *et al*., 2019, p. 7
		Changes to the group of unemployed and forms of employment	Desiere *et al*., 2019, p. 7
		Stronger activation focus	Desiere *et al*., 2019, p. 7
	Managers	Profiling is crucial to assist caseworkers	Assadi and Lundin, 2018, p. 159
		Profiling rationalizes frontline service delivery	Grundy, 2015
		Encourage jobseekers to internalise unemployment responsibility	Pultz, 2016, p. 177
	Profiling functions	Automatically differentiate the delivery of service for job seekers	Desiere *et al*., 2019, p. 20
		Generate a list of job seekers to be contacted	Desiere and Struyven, 2020, p. 6
		Decision-support system to assist caseworker discretion	Assadi and Lundin, 2018
	Implementation choices	Conceptualising profiling factors and results to users	Wijnhoven and Havinga, 2014; de Troya *et al*., 2018
		Determining the cut-off value of the profiling tool	Matty, 2013, p. 21
		Determining effective interventions, i.e., 'operational accuracy'	Matty, 2013, p. 3
	Implementation challenges	Insufficient resources for implementation	Niklas *et al*., 2015, p. 23
		Lack of personnel training	Pietersen, 2017, p. 15
		The development of a profiling model can be costly and lengthy	Desiere *et al*., 2019, p. 17
		The integration of profiling can pose challenges to organisations	Pietersen, 2017, pp. 15-16
		Questions of data use and privacy as obstacles	Grundy, 2015, p. 61
	Caseworkers as	Involvement of frontline staff	Møller *et al*., 2020

	stakeholders	The success of profiling conditions on caseworkers	Barnes *et al.*, 2015, p. ii
	Caseworkers as data collectors	Moral unwillingness to provide data to systems	Petersen *et al.*, 2021, pp. 17-18
		Caseworkers fill in provided answers and add related information	Assadi and Lundin, 2018, p. 158
		Skilled caseworkers typing the correct information on jobseekers	Boskoski and Boshkoska, 2020, p. 5
	Caseworker discretion	Discretion might hinder algorithmic precision and efficiency	Møller *et al.*, 2020, p. 1
		Profiling can underscore caseworkers' discretion	Sztandar-Sztanderska and Zieleńska, 2018, p. 2
		Profiling can support case handling and relation to jobseekers	Flügge *et al.*, 2021, p. 1
		Discretion relates to the caseworker's experience	Assadi and Lundin, 2018, p. 154
	Caseworker resistance	Terminated profiling projects	Caswell *et al.*, 2010;
		Resistance versus managerial decisions due to privacy issues	Grundy, 2015, p. 52
		Resistance and usability	Zejnilovic *et al.*, 2020, p. 6
		Reasons for none-resistance	Kuzjemski and Misuraca, 2020, p. 8
		Administrative burdens	McGuinness and Kelly, 2020, p. 11
Jobseekers	**Modes of governing**	Profiling individualises unemployment	Caswell *et al.*, 2010, p. 384; Pultz, 2016
		Profiling is a risk technology	Sztandar-Sztanderska and Zieleńska, 2020, p. 2
		Profiling can perpetuate risk and counteract its policy aims	Marston and McDonald, 2008; Rice, 2017, p. 479
		Profiling is a socio-technical system	Allhutter *et al.*, 2020, p. 13
	Evidence	Profiling lacks scientific evidence on its effectiveness	Barnes *et al.*, 2015, p. 93
		Pre-emptive provision of service and problem of undue process	Niklas *et al.*, 2015, p. 86
	Transparency and accountability	Public transparency	Henman, 2005, p. 94; Henman, 2004
		Opaque profiling process	Kuzjemski and Misuraca, 2020; Pultz, 2016, p. 176
		The opacity of profiling hinders the accountability of its creators	Allhutter *et al.*, 2020, pp. 13-14
	Privacy	Invasive PES that challenges the jobseekers' right to privacy	Niklas *et al.*, 2015, p. 25;
		Model accuracy relates to the privacy of the jobseeker	Desiere *et al.*, 2019, p. 22
	Discrimination	Positive and negative discrimination	Desiere and Struyven, 2020, p. 15
		The burden of proof of discrimination	Niklas *et al.*, 2015, p. 37
		Discrimination influences the discontinuation of a profiling tool	Kuzjemski and Misuraca, 2020, p. 8